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Full Length Research Paper

Impact of Credit Risk Modeling on the efficiency of Banks-A case of conventional Banks of Pakistan

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The purpose of the study was to examine the usage of credit risk models in the conventional banks of Pakistan and to identify the effect of credit risk modelling on the efficiency of banks. Credit risk models are used to measure and manage the credit risk taking into account the correlations in credit quality between different borrowers by considering the fact that they may operate in the same industries and / or countries and be influenced by the same economic forces. The variables that were identified for examining the effect of credit risk modelling on the efficiency of banks were PD Model, LGD Model and EAD Model. ROA and ROE were taken as the measure of bank's efficiency. Thirteen banks were selected in a sample to undertake this research study. Data were ranging from year 2012 to 2016. Dataset were consisting of 65 observations. Data were collected from the published annual financial reports of the commercial banks. Different kinds of statistical tests were applied depending upon the nature of data and objectives of the study. Frequency analysis is applied to examine the usage of credit risk models. On the basis of Hausman testing, the random effects model was used to evaluate the dependencies of variables. Pearson correlation analysis is applied to examine the strength of relationship. It was concluded from the study that the banking industry of Pakistan was not enough developed in terms of adopting the credit risk models. Another key finding of the result is that the credit risk models have a positive effect on the efficiency of banks.

Keywords: Credit, Credit Risk, Bank.

INTRODUCTION

Risk is an intrinsic part of the business of any bank. It is critical for any bank to manage its risks effectively for achieving financial soundness. (Singh, 2013) Risk is a standard deviation' or volatility of net cash flows of the firm. Risk management is thus the core business of banks and if the banks fail to adequately manage their risks then they may encounter the risk of insolvency where insolvency is defined as shortfall in fulfilling the commitment. (**Heffernan**, 2014) Banks being the financial intermediaries in any economic system are subject to various types of risks. By far the credit risk, the risk of counterparty default or customer remains the biggest risk for banks and financial intermediaries. The credit risk analysis and its continuing close examination provides the basis for long term stability of economic cycles and thus the credit cycles in banking industry. (**Reserve Bank of Australia** Bulletin, 1997)

Risk has been categorized into the following three types from their functional perspectives which are (a) Credit Risk / Counterparty Risk (b) Operational Risk and (c) Market Risk. Credit risk is the risk to each party of a contract that the other party shall not fulfill its contractual obligation. (**Dun**, 2010) Risk aggregation and Risk decomposition are the two broad strategies of risk management available to financial institutions. Risk decomposition approach is to identify the risk one by one and then handle each one of it separately whereas; risk aggregation approach is to reduce the risk by diversification. Banks were traditionally managing their risk through risk aggregation but now, with the advent of credit derivative, they are managing the risk using risk decomposition approach. (**Hulls, 2014**)

Banks have been encouraged through Basel accords for developing sophisticated systems in order to model the credit risk arising from the important affairs of their business lines. These models provide help to banks in quantifying the credit risk. Banks with the use of these models are also able to aggregate and manage the risk across product and geographical lines. The outcome of these models contribute significantly in risk management process and performance measurement processes of banks which include performance-based compensation, risk-based pricing, customer profitability analysis, capital structure decisions and active portfolio management (Basel, 1999) There are varieties of available credit risk modeling techniques however, the credit risk models such as structural models measuring the probability of default and value at risk models which measure the expected loss have gained the prominence with the advent of Basel II. (**Allen**, 2011)

Background of the Study

Throughout history, examining the borrower's ability to repay the funds has been associated with the act of lending funds. In early days, the credit risk analysis was done on the basis of financial statements and hence, the primary emphasis was given to the balance sheet of corporations. With the passage of years as the sustainability of earnings got prominence, the emphasis started to shift to the profit and loss account. Funds flow statement was emerged in late 1970 to address the insufficiencies of balance sheet and P&L. The cash flow statements have later on replaced the funds flow statements. In recent decades, Basel Committee has revolutionized the way banks manage credit risk through its accord (Generally known as Basel II and Basel III). (**Joseph**, 2014)

Banks have been encouraged through Basel accord to develop sophisticated system to model the credit risk arising from their business lines. Financial market turmoil followed by the collapse of the Bretton Woods system of managed exchange rates in 1973 has given the emergence of Basel Capital Framework. Large foreign currency losses were incurred by the banks after the collapse of Bretton Woods system. Banking license of Bankhaus Herstatt was withdrawn by the West Germany's Federal Banking Supervisory Office on 26 June 1974 after identifying that the foreign exchange exposures of bank amounted to three times of its capital. Heavy losses were also incurred by the banks outside the Germany on account of their unsettled trades with Hersatt, giving an international aspect to the turmoil. After incurring the heavy foreign exchange losses in the month of October of same year, the Franklin National Bank of New York also shut down its business. These and other disturbances in the international financial markets withdrew the attention of developed countries towards formulating a standard frame work to avoid such disruptions in future which led to the establishment of Committee on Banking Rules/Regulations and Supervisory Practices at the end of 1974. The committee was established by the governors of central banks of the G10 countries. The committee on banking regulations and supervisory practices was later on renamed the Basel Committee on Banking Supervision (BCBS). A forum to its member countries for regular cooperation on banking supervisory/managerial matters was provided by the committee. The aim of this committee was and is to boost the financial stability by improving the quality of banking supervision worldwide and the supervisory knowhow. (SBP)

Considering the financial market requirements, the Basel committee released a consultative paper to banks in July 1988 known as Basel Capital Accord (1988 Accord) requiring banks to maintain a minimum capital ratio of capital to risk-weighted assets of 8% for implementation by the end of 1992. Committee released a Revised Capital Framework in June 2004, known as Basel II. The revised capital frame work comprises of three pillars named as; (a) minimum capital requirement; (b) supervisory review; (c) and market discipline. The banks were encouraged through Basel II for developing their own internal controls and system for measurement and management of credit risk (Basel, 2014) Following two approaches have been broadly proposed under Basel II for calculating capital requirement for credit risk which is Internal Ratings Based (IRB) Approach and Standardized (STD) Approach. Internal Ratings Based Approach (IRB) is further subdivided into two approaches i.e. Foundation IRB Approach and Advanced IRB Approach. The Standardized (STD) Approach may also be called External Ratings Based Approach. Under this approach, risk weights are determined on the basis of the ratings assigned to counterparty by an external credit rating agency (ies) duly approved by the national supervisor under the guidelines issued by Basel committee. Banks using the Internal Ratings Based Approach depends on their own estimates of risk components in determining the capital requirements for a given exposure subject to certain conditions, disclosure requirements, and supervisory approval for its use. Internal Ratings Based (IRB) Approach is further subdivided into Foundation IRB approach and Advanced IRB approach. Under Foundation IRB approach, banks use their own estimates of probability of default and rely on the estimates provided by the supervisor for other risk components which are LGD & EAD. Banks using the advanced IRB approach calculate their own estimates of LGD, PD, and EAD subject to the minimum standard of risk management specified by the national supervisor. (**Dun, 2010**)

During 2008, the world economy became uncertain and affected negatively due to the increased economic downturn and global financial crisis (GFC). The greatest risks posed to banks take the form of credit risk. The crisis has clearly realized the importance of risk management. The world trade environment was deteriorated considerably after August 2007. The frequent and abrupt changes in the global financial market put the various kinds of risks to the banking industry (Ali, 2013) Global Financial Crisis given the emergence of Basel III document in December, 2010. The Basel III version issued in December 2010 was set out into following two portions: (a) A global / international regulatory framework for more robust banks and systems of banking; (b) and, international/global framework for liquidity risk measurement, standards and monitoring. The three pillars concept given by the Basel II was got revised and strengthen in the Basel III document. The enhanced Basel document provided a comprehensive framework with a numerous innovations such as; strengthening of capital, global liquidity standard, risk coverage, and leverage ratio. Banks have been encouraged through Basel accord III to measure the credit risk at portfolio level along with measuring the risk at standalone credit facility level. (State Bank of Pakistan)

Financial Structure and Capital Adequacy Reforms in Pakistan:

The economic growth and government plans for developing the country have evolved the financial system in Pakistan over the years (**Ali, 2013)** Banking system in Pakistan is of key consideration since the economy of Pakistan falls in developing country. Banking system of Pakistan contributes significantly in the economy of nation by filling a gap between the savers and the productive investments. Financial sector in Pakistan constitutes on a widespread variety of financial institutions which includes national savings schemes, brokerage houses, investments banks, stock exchanges, Islamic banks, micro-finance banks, and commercial banks which are offering a wide range of products and services. State Bank of Pakistan, the central bank of a nation is a controlling authority of a banking sector and is responsible to collect and circulate the financial information.

At present, a total of forty five banks are operating in Pakistan which includes five fully functional Islamic banks, two national banks, three provincial banks, four denationalized commercial banks, four foreign banks, twelve private commercial banks, four specialized banks, and 11 microfinance banks. In short, there are total 21 commercial banks of Pakistan. As advised by the SBP, all banks are required to continuously get themselves credit rated from the credit rating agencies available on the its panel. Two credit rating agencies are available on the panel of SBP which are JCR VIS and Pakistan Credit Rating Agency (PACRA). Credit rating may be defined as an independent opinion expressed by the professional bodies such as credit rating agencies stating about the capacity of an entity to meet its liabilities and is based on various qualitative and quantitative factors. Banks / DFIs are rated on yearly basis and their rating is updated within six months from the date of close of each financial year. (SBP)

Reason behind selecting the banking sector of Pakistan was that the banking sector of Pakistan has undergone the number of radical changes over a period of 69 years such as denationalization, nationalization, privatization and the introduction of branchless banking and Islamic banking. A reasonable performance was recorded by the banking sector in the last quarter of year 2016 with a highest quarterly growth in advances to private sector in the last 10 years. Most of the increase in assets was due to the growth in advances to private sector. The increase in net advances to Rs.5,499 billion in Q4CY16 from Rs. 4,447 billion in Q4CY14 has improved the bank's total assets to Rs. 15,831 billion in Q4CY16 from Rs. 12,106 billion in Q4CY14. Banking sector profitability was remained narrow due to reduced quantum of investment and low interest rate. A decline in non-performing loan ratio has been observed which has resultantly improved the credit risk profile of banking sector. If we see at solvency side, a minor reduction in capital adequacy ratio has been observed due to increase in advances. Capital adequacy ratio was 16.7% which is still above the minimum required level of capital adequacy i.e. 10.65%. (State Bank of Pakistan, 2016)

Basel I was implemented in Pakistan by SBP in 1997 through its BPRD Circular # 36 of November 4, 1997. Guidelines issued by the SBP through this document were only meant for credit risk faced by the banks. Later on, SBP has issued a new of instructions containing another version of Basel I framework through its BSD Circular # 12 of August 25, 2004. The instructions issued were specifying the criteria for calculating the risk weighted assets for market risk as well as credit risk. Implementation of Basel II in Pakistan was effected in year 2008 through SBP BSD Circular # 8 of June 27, 2006. The banks have been advised through these guidelines to compute their risk based capital, the capital adequacy ratio (CAR) for market, credit, and operational risk as proposed under pillar I of Basel accord. The remaining risks are to be covered under pillar II of Basel. Basel III implementation in Pakistan is in a phased manner staring from December 31, 2013 to December 31, 2019 requiring banks to increase their capital adequacy ratio (CAR) and capital conversion butter (CCB) from 10% to 12.50% in a gradual manner. The capital adequacy framework applies on all banks both at standalone as well as at portfolio (Consolidated) level. (State Bank of Pakistan)

An Overview of Progress on Credit Risk Model Development:

Banks and other institutions attitude towards credit risk has been changed in recent years with the publication of Basel Capital Accord in 2004 (Basel II). Banks were required to compute their own estimates of the credit risk parameters on the basis of Basel regulation and as advised under the internal rating-based approach. Banks evaluating their own estimates are able to more accurately align their regulatory capital with the underlying risk in a credit portfolio. Banks were permitted under Basel II to deploy their own credit risk models. Banks using these models are able to differentiate the risks in a better way, considering the consequences from the diversification of bank's portfolio. Credit risk estimation techniques have been changed in recent years which have resulted into the expansion of new models for evaluation and estimation of the probability of default of individuals or companies and the use of new parameters for identifying the possible losses. Credit risk main components are loss given default (LGD) and the probability of default (PD). Loss given default represents the proportion of an exposure which will not recovered in case of borrower's default. Previously, attention was given to the estimation and modelling of the probability of default, considering the loss given default as constant and exogenously given. The lack of studies on LGD modeling in past may be mainly due to the fact that it is always difficult to separate loss given default and probability of default on the basis of a price of single financial instrument. (Misankova, 2015)

Probability of Default (PD), Exposure at Default (EAD), and Loss Given Default (LGD) are the three main variables affecting the credit risk of a financial asset. Loss Given Default can be mathematically expressed as one minus recovery rate in the event of default. Initially significant attention was given to the estimation of probability of default. Credit risk models first category is based on the Merton original framework developed in 1974 using the principles of option pricing (Black and Scholes, 1973). This model works on the assumption that default occurs only when the assets value of the firm decreases below its liabilities. In addition to Merton (1974) work, this kind of models is including the work of Vasicek (1984), Geske (1977), and Black and Cox (1976). Vasicek (1984) familiarizes the difference between long and short term liabilities; Geske (1977) introduces the interest paying debt; Black and cox provides the possibility of more complex capital structures with subordinated debt. Under these models, all the relevant credit risk elements including recovery at default and default are the function of structural characteristics of the firm which are leverage (financial risk) and asset volatility (business risk). The recovery rate and probability of default are inversely related to each other in Merton framework. These models weren't much appreciated due to following assumptions; default at the maturity of debt, complex capital structure; absolute priority rules at the time of default, and the distribution is lognormal instead of fat tailed distribution which inclines to overstate the recovery rate. The second generation structural model works under the assumption that default may occur at any time between the issuance and maturity of debt. These models assume that default occurs when the value of firm's assets fall below the level of lower threshold. These second generation models include the work of Hull and White (1995), Longstaff and Schwartz (1995) Kim et al. (1993), Nielsen et al. (1993), and others. These models assume that the recovery rate at the time of default is independent from the firm's asset value and is exogenous. Under these models, the rate of recovery in the event of default is exogenous and independent from the asset value of a firm. The recovery rate is a fixed ratio of outstanding exposure value and independent from the probability of default. Despite the second generation models significantly improved the original framework of Merton but still these models suffered from the following three kinds of shortcomings; (a) Parameter estimation for the value of firm's asset which is not observable, (b) not incorporating the credit rating change, and (c) default cannot be predicted well before the time it happens as value of the firm is assumed continuous in time in structural form models. The attempt to overcome these shortcomings had given the emergence of reduced form model. Reduced form models assume recovery rate as independent from the default probability, treating it as an exogenous variable thus do not condition the default with the firm's value. This model works under the assumption that RR is dependent on the value of the default able claim. Recovery rate and default probability are to be correlated as both depend on macroeconomic or firm specific. Credit risk models developed in the second part of 1990s were aimed at measuring the potential loss that the credit exposure portfolio could experience within a given time horizon generally of one year with a predetermined confidence level. These value at risk (VaR) models include CreditMetrics® by J.P. Morgan, CreditPortfolioView® by McKinsey's, CreditRisk+® by Credit Suisse Financial Products, and CreditPortfolioManager® by KMV. Credit VaR models can be largely seen as reduced form models. In reduced form models, recovery rate is normally taken as a stochastic variable independent from default probability or an exogenous constant parameter. CreditPortfolioManager®, CreditPortfolioView®, and CreditMetrics® are among those credit risk models treating recovery rate in the event of default as a stochastic variable independent from the default probability and generally modelled through a beta distribution. Others credit risk models such as CreditRisk® consider the recovery rate as a constant parameter that must be stated as an input for each single credit exposure. (Altman, 2004)

External ratings and the financial statement analysis models are the historically prominent methods for analyzing the credit risk. External ratings agencies such as Moody's, Fitch, or Standard & Poor's (S&P) provide the external ratings. The financial statement analysis models give a rating on the basis of financial statement analysis of individual borrowers using the techniques such as the Moody's RiskCalc and Altman Z score. With the arrival of Basel II, the credit risk models such as the structural models, measuring the probability of default and value at risk models attained a great importance. Structural models work on the option pricing methodologies and collect the information from market data. It is the capital structure that triggers the default when the value of obligor or firm decreases below its financial obligation such as the KMV and Merton models. VaR models measure the expected losses over a given time period at a given level of tolerance. These models include the CreditMetrics model by JP Morgan which applies a Transition Matrix, and the CreditPortfolioView model wherein transition approach includes the macroeconomic factors. (Allen, 2011)

Significance of the Study

The pace of change in the behavior of banks towards managing the credit risk is considered as an expected response to an environment wherein competition in terms of providing the financial services facilities is on an increasing trend. This increased competition arise the need for banks to look for new and profitable business opportunities along with properly measuring the associated risks. The improved ability of a bank to assess risk and return connected with the activities of various kinds will make transparent the nature and comparative sizes of implied internal benefits. (Reserve Bank of Australia Bulletin, 1997) Credit risk exposure remains one of the main sources of problems to banks throughout the world. Banks should now have developed an awareness of the need to identify, evaluate, monitor and control the risk of credit exposure. Banks are required to determine that they keep the adequate capital against these risks and they are also to get themselves ensured that they are well compensated for the risks incurred. (Basel, 2000) Commercial banks are among the key suppliers of credit in any country as they supply finance for business requirement. Considering public confidence on banks, Governments are very much concerned about the banking sector exposure of credit risk and therefore, measuring and monitoring the non-performing loan or bad debts level on an ongoing basis. (Joseph, 2014). One of the major risks to banks is a credit risk and therefore, regulators are continuously insisting banks on improving its measurement in order to quantify the amount of capital that the bank should hold. Credit risk may not only occur due to default of counterparty on its obligations but it may also be treated as risk of loss due to decrease in the credit quality of a borrower. (Bessis, 2002) Credit risk is considered as one of the biggest risks facing to banks and to manage it, the most regulatory capital is required. (Hulls, 2014). The role of commercial banks is very significant in the economy of developing countries with privatized economies and thus, the social wellbeing of these countries depends on the commercial banking sector behavior of a country. Banks failure in such settings affects the overall social structure of a country. It is therefore, important that the credit or lending decisions should be made with prudence as much as possible without affecting the efficiency and effectiveness of the decision making process. (Emel et. al., 2003)

Financial institutions and banks are particularly exposed to credit risk as bad debt is the common problem faced by the all banks in world. One of the fundamental banking risks is a Credit risk which contains majority of the banks losses. Banks are therefore, required to continuously improve their practices and models for managing the credit risk and always look for new and effective ways to avoid it. (Kliestik, 2015) Credit risk may be considered as the most important type of risk which has been existed in trade transactions, commerce, and finance. A significant progress has been made in recent days with regard to credit risk management techniques which have led to the establishment of new methods for estimating the potential bankruptcy of borrowers including entities and the parameters stating possible losses. (Spuchľakova, 2015)

Banks have been realized form the significance of credit problems experienced by them during Global Financial Crisis that it is really very important to accurately measure and provide for credit risk. Each model has different criteria for evaluation and an understanding of disadvantages and advantages of various models can help the banks in choosing between the available credit modeling techniques. (Allen, 2011)

Credit risk models contribute significantly in enhancing the internal risk management systems in banks. Models measure the risk on a portfolio level and thus, provide a satisfactory measure of concentration risk and diversification benefits of a portfolio of exposure as compared to the traditional technique constituting of limit system. It also helps the banks in estimating the amount providing for unexpected losses. Researcher is of further view that banks especially internationally active could do well using model based approach. (**Shilpi**, 2014) Credit risk models are generally used in financial institutions for evaluating the economic capital needed to face the risk connected with their portfolio of credit. (**Altman et. al., 2004**).

It is required to depend on the algorithms and model rather than on human judgment in consumer lending because of huge number of decisions involved. Banks and other financial intermediaries should focus on the default probability of the borrowers. There are several models available to analyze credit risk, some of which are qualitative models, and some are quantitative models. Qualitative models indicate borrower specific factors and market specific factors. Researcher further says that need for accurate decision support model doesn't arise only at the time of evaluating the credit admission but also for observing the ongoing credit quality of the customers. Credit risk modelling improves the internal risk management and plays an increasingly important role in performance evaluation processes which include customer profitability analysis, performance based compensation, active portfolio management, capital structure decision, and risk based pricing. Banks before setting up the models for practical use must ensure that the proposed model is based on the sound concepts, its results are validated through testing and it produces the capital requirement which is comparable across institutions. Researcher further says that data limitation and model validation are the significant hurdles in the application of credit risk models. (Basel Committee on Banking Supervision, 1999) Financial crises that have been experienced in the recent or past realized to banks the importance of properly recognizing, predicting and estimating the risks. Sustainability of the business activities of financial institutions depend on the management of risk and prediction of potential losses. Multiple variables are analyzed to quantify the credit losses. Credit risk main components are the loss given default (LGD) and the probability of default (PD). These both components are included in the credit spread and make the difference between market price of default able and default free bond. (**Misankova, 2015**) The advancement in credit risk modeling brings more discipline in credit risk pricing and promotes the diversification by penalizing the credit risk concentration with more allocation of economic capital. Before relying on credit risk models, the regulators are to reassure that the models are working on sound concepts, results are validated through testing, and the economic capital allocation produced is comparable across the institutions.

After a detailed review of related literature, researcher is of view that a very few research studies have been undertaken on the topic under discussion especially in Pakistan. Haven't even found a single study empirically investigating the relationship between credit risk modeling and its impact on the efficiency of banks however, research work comparing the famous models is available. This has made the researcher to take the subject topic as a challenge and proceed with it. This research study has been undertaken to evaluate the usage of credit risk modeling techniques and methodologies in conventional banks in Pakistan for measuring the credit risk at both single credit facility level and portfolio level. It provides an insight into the vast topic of credit risk, its modeling and methodologies which may be helpful to the decision makers of conventional banks in Pakistan for making right choice for their banks. Understanding the credit risk becomes more important because of increase in the variety of counterparty types and the obligation forms. One cannot be in position to averse / mitigate the risk until unless he/she is fully aware about risk factors and the risk itself. State Bank of Pakistan may also take the benefits from this research study as it entails the implementation status of Basel Accord in Pakistan.

Objectives of the Study:

Banks are the profit seeking organizations and therefore, they attempt to improve the risk and return trade off in their decision making processes. It may be a hard for the banks to live without handling these risks as today's risk may become the tomorrow's realities.

Following are objectives of the study:

1. To examine the usage of credit risk models in the conventional banks of Pakistan for measuring the credit risk.
2. To understand the effect of credit risk modeling on the efficiency of conventional banks in Pakistan
3. To find out the effect of credit risk modeling on the efficiency of conventional banks in Pakistan.
4. To find out the effect of each key parameter of credit risk model on the efficiency of conventional banks in Pakistan.

Problem statement

The significant problems faced by the banks during Global Financial Crisis have highlighted the importance of measuring and providing for credit risk. Credit risk models are generally used in financial institutions for evaluating the capital required to deal with the risk associated with their credit portfolio. Banks in Pakistan are at their innate stage in credit risk model development and just following the standardized and foundation IRB approach. An effective credit risk model enables the bank to improve its efficiency by proactively identifying, measuring and providing for capital to sustain against unexpected financial loss. A significant lag has been observed in the area of credit risk modeling in Pakistan as compared to other developed countries and thus, requiring the immense need of a research work. This research study would be designed to analyze the impact of credit risk modeling on the efficiency of conventional banks in Pakistan.

LITERATURE REVIEW

Bastos (2010) estimated the ability for regression of a parametric fractional response and a tree model of nonparametric regression for forecasting the loan credit losses of a bank. The paper also concluded that the fractional response regressions are appropriate for the longer horizons. The out-of time predictive ability was examined for one year recovery horizon. The paper noticed that the estimation results of regression tree are best in terms of predictive accuracies for out-of-time. **Tong (2016)** attempted to explore an EAD model that pays no attention to prepare CCF and only focus on the distribution of EAD. This study proposed the zero-adjusted gamma model as it was found more accurate than the benchmark models. However, this paper found that the segmented approaches can be used for performance improvements. This research study concluded that direct EAD models (without the formulation of credit conversion factor) can be as an alternative to models based on CCF or even both can be combined. **Tanoue** (2017) conducted the research study to analyze the influencing factors of LGD and to develop a (multi-stage) model to predict LGD and expected loss (EL). The dataset used in this study consists of loan data from three Japanees banks for the period from 2004 to 2011. (This research study has shown that the LGD level differs from year to year; however, it could be more interesting if the researcher address the relationship between loss given default and the business cycle.) **Drake** (2009) examined the efficiency of banking system of Japan using the slacks-based measure, by applying the three comparative bank modelling methodologies which are intermediation approach, production approach and revenue based approach. The paper revealed that different methodological approaches to the inputs and outputs specification in reference to the non-parametric banking efficiency analysis can make the difference in: mean efficiency scores; the efficiency scores dispersion; and the ranking of banks. It is concluded from the results that particular methodological approach affects the relative efficiency analysis and model specification adopted and hence, is of considerable significance in the context of policy response. **Fiordelisi (2013)** had found that higher efficiency levels, where cost is minimized and profit and revenue is maximized, have a significantly positive relationship with the survival probability of cooperative banks. It has also been revealed by the researcher that capital adequacy decreases the default probability, supporting the opinion that the reduced moral hazard problems and absorbency of additional loss are associated with higher capital buffers. **Dermine** (2005) claimed that it is the first empirical paper which has studied bank loan losses-given default in Europe. This paper has also revealed that the bank incur direct costs in recoveries on bad and doubtful loans. The explanatory variables of recovery rates i.e. Type of guarantees and collateral support, size of loan, the industry element, and the age of the borrower has been tested empirically. **Crouhy** (2000) reviewed the methodologies of the current credit Value-at-risk and made a analysis of current credit risk models on comparative basis. ? In this research paper, research has theoretically analyzed the credit risk models by discussing their approaches and assumptions on which these models are working. It could be more interesting if the researcher makes his study empirical by actually analyzing the comparative impact of these models in estimating the default or expected default. **Fatemi** (2006) investigated the present practices of credit risk management used by the US-based financial institutions. It could be more worth reading if the researcher makes a comparative impact analysis of the credit risk models on the non-performing loan (NPL) ratio. This will not only give the practical knowledge to the reader(s) and the stakeholders to better understand which model works efficiently and under what conditions. **Zhao** et al. (2014) investigated the usage of credit line in middle-market corporate borrowers. Focus of the study was on credit line usage of unlisted and middle market firms. The study concluded that the riskier borrowers avails a higher percentage of their credit lines. Usage ratios are higher during economic downturn especially for non-defaulted firms. Another interesting observation made in this study is that internally rated firms as the lender drawn below the credit lines more than those rated below pass grade. It was suggested in the paper that bank should closely monitor lines with poorer internal ratings. **Karminsky** (2014) found that quadratic U-shaped relationship exist between a capital adequacy ratio of bank and its probability of default. This paper has revealed that the banks with substantial proportion of loans (overdue) or commercial securities have a higher PD. **Sun** (2011) has investigated the risk role in determining the cost efficiency in international banks of 8 emerging Asian markets (those have publicly listed commercial banks) i.e. China, Indonesia, India, Malaysia, South Korea, Philip pines, Thailand and Taiwan. It was concluded from the empirical study that risk measures have substantial effects on the level and variability of efficiency of bank which may differ across the countries.

Gunay (2012) applied a new approach in efficiency analysis and incorporated credit risk as an undesirable by-product in a multi-output model. The study has emphasized on using the variable returns to scale (BCC) model instead of constant returns to scale (CCR) model. This study revealed the increasing trend in the efficiency of banks and both models during the post-crisis period. **Nguyen** (2015) examined the interrelationship among default risk, capital ratio, and efficiency. This paper has revealed that there is a two-way negative relationship between default risk and efficiency and between capital ratio and default risk. Two-way positive relationship exists between profit efficiency and capital ratio. The study found that probability of default risk is greater and capital ratio is lower in public banks. However, Public banks have higher efficiency level than private banks. This research study supported to ratio of capital as a smart tool for improving efficiency and decreasing default risk of the Indian system of banking. **Saeed** (2014) examined the linkage between default risk and efficiency in Islamic banks (IBs) and conventional banks (CBs) of Gulf Cooperation Countries (GCC) and three other non-GCC countries during the period 2002–2010. **Erdinc (2016)** investigated the significance of using the Internal Rating Based methodologies to reduce the aggregate non-performing loans level in a number of advanced and emerging European economies. A significant lag in terms of adoption of IRB approach was noticed in Emerging Europe as compared to the Eurozone economies. It has been statistically confirmed in this research study that the banks using IRB approach are contributing significantly in reducing the non-performing loans aggregate amount which is in turn contributing significantly to improve the stability, solvency and profitability of banks with the added benefits of increasing the economic growth and resources allocation in better way. **Leow** (2014) investigated the parameter estimation stability of discrete survival models before and after the credit crisis of year 2008. The results of this study stated that changes in the distribution of predicted default probabilities was due to the reason of cohort quality admitted under the different conditions of economy, macro economy and the estimated parameters. The study also implied that models are still not able to model the various effects adequately arising from the borrower type, and macroeconomic conditions. (It could be more interesting if the researcher explores and quantifies the effect of variation in macro economy and quality of cohort on the default probability for calculating the loss.

RESEARCH METHODOLOGY

Nature of Study

Study undertaken was the quantitative and qualitative in nature as consisting of analysis of financial annual reports of banks in terms of measures taken for credit risk modeling such as using internally developed models for measuring Probability of Default, Loss Rate Given Default, and Exposure at Default model. Moreover, information related to bank's efficiency in terms of ROA (Return on Asset) and ROE (Return on equity) were also collected through banks' annual financial reports.

Source of Data:

Data were collected from the published annual financial reports of the commercial Banks selected for the study.

Data Range:

The dataset was consisting of time period ranging from year 2012 to 2016.

Population:

Banking sector of Pakistan was taken as a population.

Sample:

Data were collected through random sampling technique.

Sample Size:

Sample size considered for the study was 62%. The banks selected in the sample were 13 in number which are MCB Bank, Soneri Bank, JS Bank, Habib Bank, Faysal Bank, Bank of Khyber, Askari Bank, Bank Alfalah, Allied Bank, Standard Chartered Bank, Summit Bank, Silk Bank, and Samba Bank

Unit of Analysis:

Unit of the study were the commercial banks of Pakistan. There are total 21 private & public sector commercial banks of Pakistan out of the strength of 45 banks. In Pakistan, there are five public sector commercial banks, 16 private commercial banks, four specialized banks, five fully functional Islamic banks, four foreign banks, and 11 microfinance banks.

Model:

Frequency analysis was calculated for examining the usage of credit risk models in the commercial banks of Pakistan. Descriptive analysis was used to describe the basic features of data. Random Effects Model was used to estimate the relationship among variables. Hausman test was applied to determine whether to use fixed effect model or random effect model. Hausman test suggested applying the random effect model.

The random effects model is:

$$\hat{Y}_{i,t} = a + b_1 x_{1i,t} + b_2 x_{2i,t} + b_3 x_{3i,t} + u_{i,t} + \varepsilon_{i,t}$$

Pearson r correlation test was applied to measure the strength of a relationship between two variables. The value of 'r' always ranges from -1 < 0 < 1 wherein -1

implies that the relationship between predictor and criterion is perfectly negative, 1 implies that the relationship between predictor and criterion is perfectly positive and 0 implies that no relationship exists between predictor and criterion.
Following is the formula to compute the Pearson R test:

$$r = \frac{N\Sigma xy - \Sigma(x)\Sigma(y)}{\sqrt{[N\Sigma x^2 - (\Sigma x)^2]\,[N\Sigma y^2 - (\Sigma y)^2]}}$$

Hypothesis

Ho_1: There is an existence of probability of default model in the conventional banks of Pakistan.
$H1_1$: There is no existence of probability of default model in the conventional banks of Pakistan.
Ho_2: There is an existence of Loss Given Default model in the conventional banks of Pakistan.
$H1_2$: There is no existence of Loss Given Default model in the conventional banks of Pakistan.
Ho_3: There is an existence of Exposure at Default model in the conventional banks of Pakistan.
$H1_3$: There is no existence of Exposure at Default model in the conventional banks of Pakistan.
Ho_4: There is an effect of credit risk modelling on the return on asset (ROA) of conventional banks in Pakistan.
$H1_4$: There is no effect of credit risk modelling on the return on asset (ROA) of conventional banks in Pakistan.
Ho_5: There is an effect of credit risk modelling on the return on equity (ROE) of conventional banks in Pakistan.
Ho_5: There is no effect of credit risk modelling on the return on equity (ROE) of conventional banks in Pakistan.
Ho_6: There is an effect of probability of default (PD) model on the return on asset (ROA) of conventional banks in Pakistan.
$H1_6$: There is no effect of probability of default (PD) model on the return on asset (ROA) of conventional banks in Pakistan.
Ho_7: There is an effect of probability of default (PD) model on the return on equity (ROE) of conventional banks in Pakistan.
$H1_7$: There is no effect of probability of default (PD) model on the return on equity (ROE) of conventional banks in Pakistan.
Ho_8: There is an effect of loss given default (LGD) model on the return on asset (ROA) of conventional banks in Pakistan.
$H1_8$: There is no effect of loss given default (LGD) model on the return on asset (ROA) of conventional banks in Pakistan.
Ho_9: There is an effect of loss given default (LGD) model on the return on equity (ROE) of conventional banks in Pakistan.
$H1_9$: There is no effect of loss given default (LGD) model on the return on equity (ROE) of conventional banks in Pakistan.
Ho_{10}: There is an effect of exposure at default (EAD) model on the return on asset (ROA) of conventional banks in Pakistan.
$H1_{10}$: There is no effect of exposure at default (EAD) model on the return on asset (ROA) of conventional banks in Pakistan.
Ho_{11}: There is an effect of exposure at default (EAD) model on the return on equity (ROE) of conventional banks in Pakistan.
$H1_{11}$: There is no effect of exposure at default (EAD) model on the return on equity (ROE) of conventional banks in Pakistan.

Variables:

The Independent Variables (Also called the Predictor):

The independent variables considered for this study were the Probability of Default (PD) Model, Exposure at Default (EAD) Model, and Loss Given Default (LGD) Model. These were the dummy variables. We may also say these were the attribute variables / binary variables consisting of denotation of 0 & 1 wherein, 1 represents the existence of model and 0 represents the non-existence of model.

- ***Probability of default (PD):*** The probability of default (PD) can be expressed as the statistical percentage of the probability of borrower defaulting, usually within a time horizon of one year (Joseph, 2013)
- ***Loss Given Default (LGD):*** Loss given default (LGD) is the estimated amount of loss expected if a credit facility defaults. (Joseph, 2013)
- ***Exposure at default (EAD):*** Exposure at default represents the expected level of usage of the facility utilization when default occurs. (Joseph, 2013)

The Dependent Variables (Also called Criterion):

Dependent variables considered for this study was the Return of Asset (ROA) and Return on Equity (ROE), the measure of bank’s efficiency.

- ***Return on Asset (ROA):*** Also called the return on investment (ROI). It measures the overall effectiveness of management in generating profits with its available assets. (Gitman, 2006)

Formula for measuring the Return on Asset (ROA) is as under:

$$ROA = \frac{Earnings\ available\ for\ common\ stockholders}{Total\ assets}$$

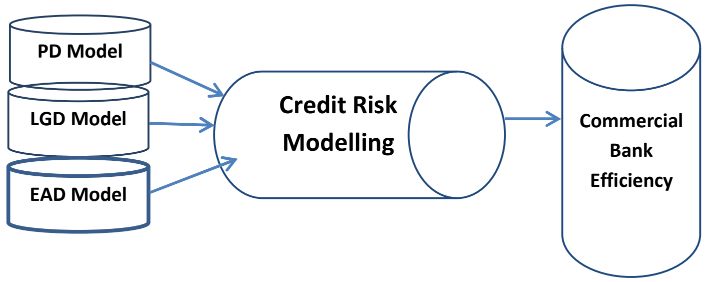

Figure 1 : Conceptual Framework

Table 1 : Frequency Analysis for Probability of Default (PD) Model

		Frequency	Percent	Valid Percent	Cumulative Percent
PD Model	.00	59	90.8	90.8	90.8
	1.00	6	9.2	9.2	100.0
	Total	65	100.0	100.0	

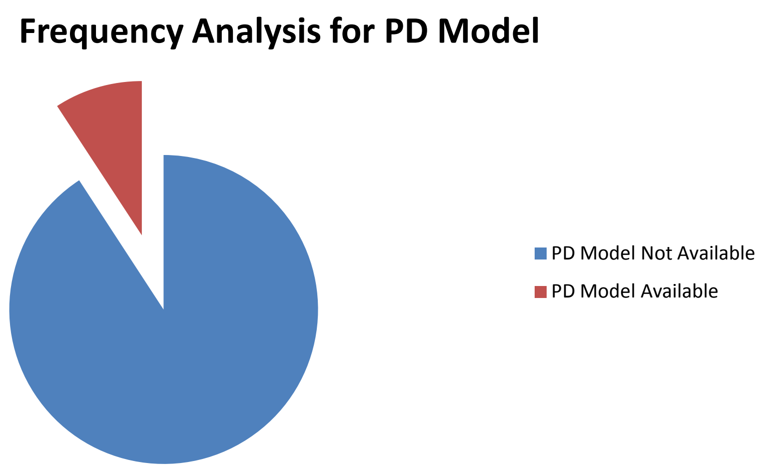

Figure 2 : Frequency Analysis for PD Model

➢ ***Return on Equity (ROE):*** It measures the return earned on the common stockholders' investment in the firm. (Gitman, 2006)

Formula for measuring the Return on Equity is as under:

$$ROE = \frac{Earnings\ available\ for\ common\ stockholders}{Common\ stock\ equity}$$

Rationality behind the selection of variables:

Internal Rating-Based (IRB) approach assumes the sophisticated and advanced risk management system in the bank. The main components of such systems are; (a) the Loss Given Default (LGD), (b) Probability of default (PD), and (c) the Exposure at Default (EAD) (Joseph, 2014) Probability of default, exposure at default, and loss given default are the key parameters for managing the credit risk. Probability of default is the probability of a company to default within the certain time period, usually of one year. Loss given default is the percentage of loss suffered comparative to the exposure at default. Exposure at default expresses the outstanding amount of obligation in the event of default (**Misan**kova, 2015) Credit risk of financial assets is affected by the three main variables which include the loss given default (LGD), probability of Default (PD), and the exposure at default. (Altman, 2004) The researcher in the study 'The

Table 2 : Frequency Analysis for Loss Given Default (LGD) Model

		Frequency	Percent	Valid Percent	Cumulative Percent
LGD Model	.00	60	92.3	92.3	92.3
	1.00	5	7.7	7.7	100.0
	Total	65	100.0	100.0	

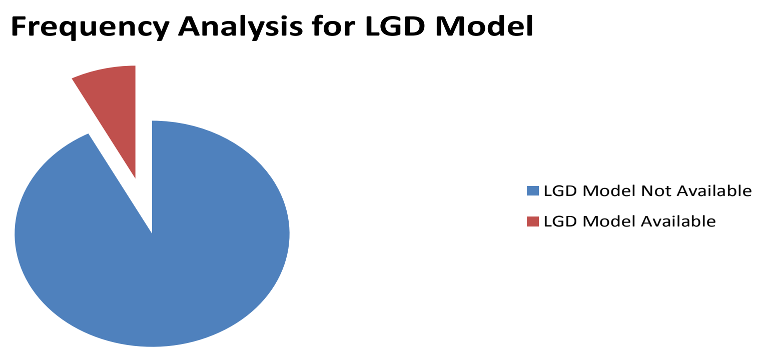

Figure 1 : Frequency Analysis for LGD Model

Table 3 : Frequency Analysis for Exposure at Default (EAD) Model

		Frequency	Percent	Valid Percent	Cumulative Percent
EAD Model	.00	60	92.3	92.3	92.3
	1.00	5	7.7	7.7	100.0
	Total	65	100.0	100.0	

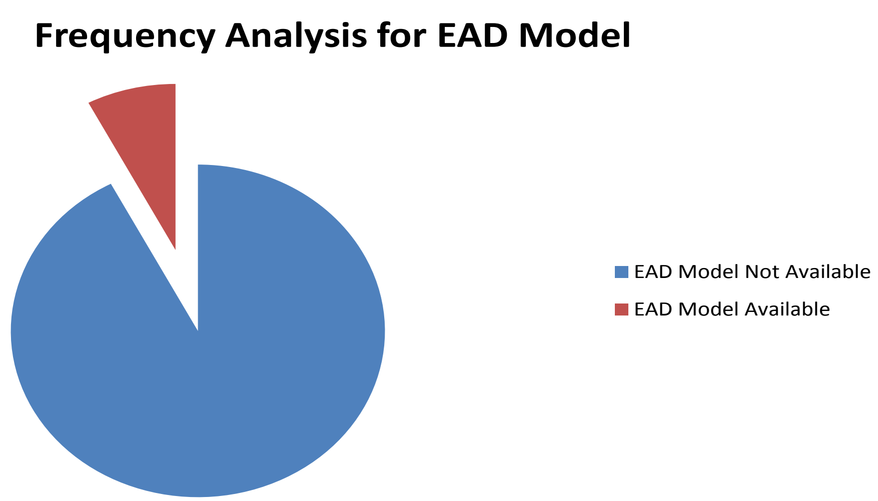

Figure 4 : Frequency Analysis for EAD Model

impact of credit risk management on the commercial banks performance in Nigeria' measured the performance of commercial banks by using the return on asset (ROA) and return on equity (ROE) as performance indicator. In the research paper, the effect of credit risk management on financial performance of the Jordanian

Table 4 : Bank-wise status of credit risk modelling over the period of five years (2012 to 2016)

	2012			2013			2014			2015			2016		
	PD	LGD	EAD	PD	LGD	EAD	PD	LGD	EAD	PD	LGD	EAD	PD	LGD	EAD
Samba Bank	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Silk Bank	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Standard Chartered Bank	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Summit Bank	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Allied Bank Ltd	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Bank Alfalah Ltd.	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Askari Bank Ltd	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Bank of Khyber	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Faysal Bank	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Habib Bank Ltd.	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
JS Bank	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
MCB Bank	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0
Soneri Bank	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

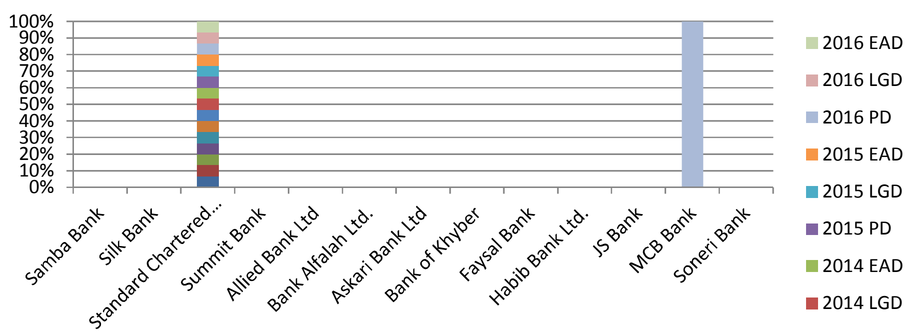

Figure 5 : Bank-wise status of credit risk modelling

Table 5 : Bank-wise status of PD Model over the period of five years (2012 to 2016)

	2012	2013	2014	2015	2016
Samba Bank	0	0	0	0	0
Silk Bank	0	0	0	0	0
Standard Chartered Bank	1	1	1	1	1
Summit Bank	0	0	0	0	0
Allied Bank Ltd	0	0	0	0	0
Bank Alfalah Ltd.	0	0	0	0	0
Askari Bank Ltd	0	0	0	0	0
Bank of Khyber	0	0	0	0	0
Faysal Bank	0	0	0	0	0
Habib Bank Ltd.	0	0	0	0	0
JS Bank	0	0	0	0	0
MCB Bank	0	0	0	0	1
Soneri Bank	0	0	0	0	0

commercial banks, the researcher examined the financial performance of commercial banks by using the ROA and ROE as the measure of financial performance After having a review of related literature, the researcher has

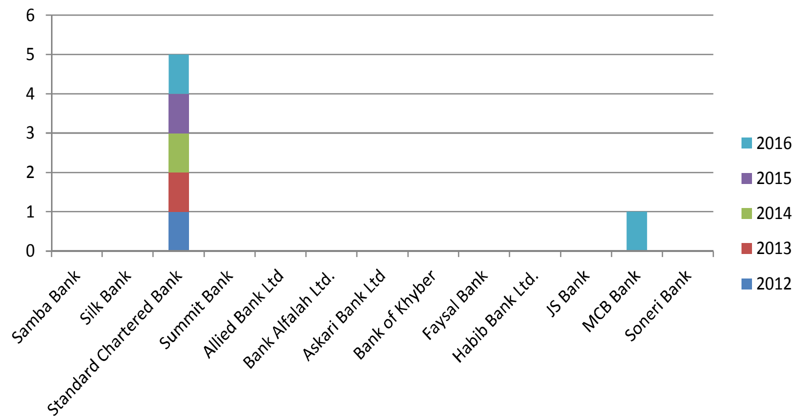

Figure 6 : Bank-wise status of PD Model

Table 6 : Bank-wise status of LGD Model over the period of five years (2012 to 2016)

	2012	2013	2014	2015	2016
Samba Bank	0	0	0	0	0
Silk Bank	0	0	0	0	0
Standard Chartered Bank	1	1	1	1	1
Summit Bank	0	0	0	0	0
Allied Bank Ltd	0	0	0	0	0
Bank Alfalah Ltd.	0	0	0	0	0
Askari Bank Ltd	0	0	0	0	0
Bank of Khyber	0	0	0	0	0
Faysal Bank	0	0	0	0	0
Habib Bank Ltd.	0	0	0	0	0
JS Bank	0	0	0	0	0
MCB Bank	0	0	0	0	0
Soneri Bank	0	0	0	0	0

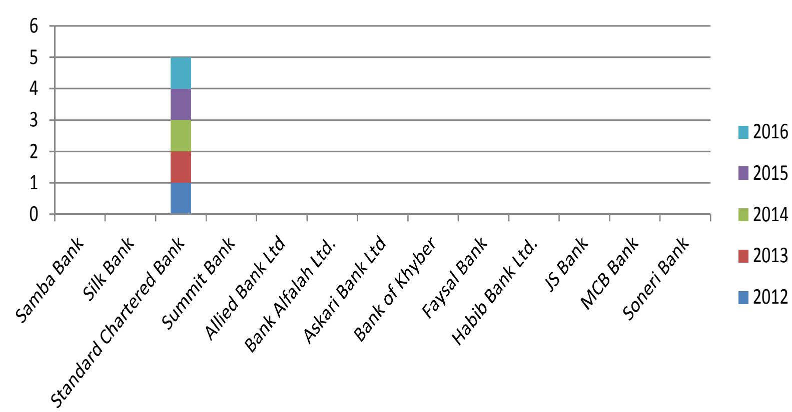

Figure 7 : Bank-wise status of LGD Model

considered the PD, LGD, and EAD as independent variables and taken the ROA and ROE as the measure of

Table 7 : Bank-wise status of EAD Model over the period of five years (2012 to 2016)

	2012	2013	2014	2015	2016
Samba Bank	0	0	0	0	0
Silk Bank	0	0	0	0	0
Standard Chartered Bank	1	1	1	1	1
Summit Bank	0	0	0	0	0
Allied Bank Ltd	0	0	0	0	0
Bank Alfalah Ltd.	0	0	0	0	0
Askari Bank Ltd	0	0	0	0	0
Bank of Khyber	0	0	0	0	0
Faysal Bank	0	0	0	0	0
Habib Bank Ltd.	0	0	0	0	0
JS Bank	0	0	0	0	0
MCB Bank	0	0	0	0	0
Soneri Bank	0	0	0	0	0

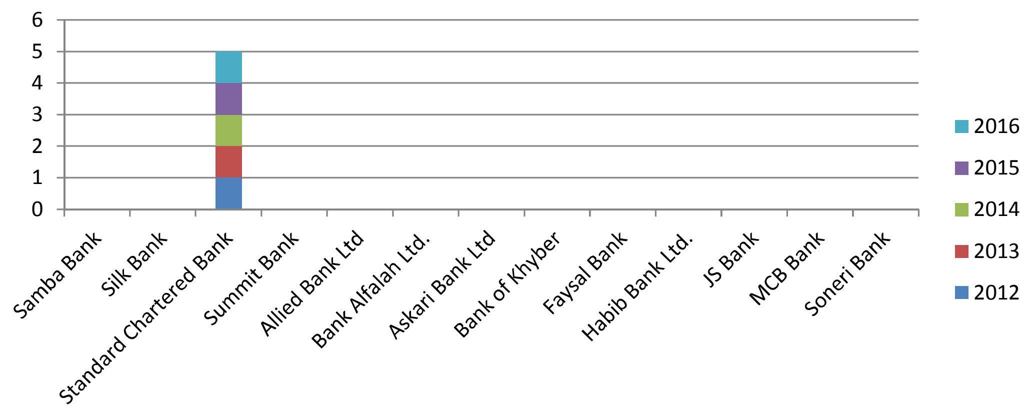

Figure 8 : Bank-wise status of EAD Model

Table 8 : Descriptive Analysis for all variables

	N	*Minimum*	*Maximum*	*Mean*	*Std. Deviation*
PD Model	65	.00	1.00	.0923	.29171
LGD Model	65	.00	1.00	.0769	.26854
EAD Model	65	.00	1.00	.0769	.26854
ROE	65	-94.34	29.96	9.1935	19.37186
ROA	65	-2.03	2.94	.9014	1.06976
Valid N (listwise)	65				

efficiency of commercial banks for this research study.

Conceptual Framework:

Statistical Analysis:

Descriptive and inferential analysis was done using the Stata software & SPSS software. The stata software was of version 10 whereas, SPSS version was 15. Descriptive analysis and correlation was computed through SPSS software. Random effect model was applied in stata.

RESULTS

This chapter deals with the analysis and interpretation of the data. The study was undertaken with the objective to

Table 9 : Random Effect Analysis for ROA

```
. xtreg roa d1 d2 d3 d4 d5, re
note: d5 omitted because of collinearity

Random-effects GLS regression                   Number of obs      =        65
Group variable: i                               Number of groups   =        13

R-sq:  within  = 0.0000                         Obs per group: min =         5
       between = 0.0000                                        avg =       5.0
       overall = 0.0358                                        max =         5

                                                Wald chi2(4)       =     10.23
corr(u_i, X)   = 0 (assumed)                    Prob > chi2        =    0.0368
```

roa	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
d1	-.1746154	.1985596	-0.88	0.379	-.5637851	.2145543
d2	-.4030769	.1985596	-2.03	0.042	-.7922466	-.0139072
d3	.1592308	.1985596	0.80	0.423	-.2299389	.5484004
d4	.0792308	.1985596	0.40	0.690	-.3099389	.4684004
d5	0	(omitted)				
_cons	.9692308	.3008967	3.22	0.001	.3794842	1.558977
sigma_u	.95954986					
sigma_e	.50622965					
rho	.7822706	(fraction of variance due to u_i)				

Table 10 : Random Effect Analysis for ROE

```
. xtreg roe d1 d2 d3 d4 d5, re
note: d5 omitted because of collinearity

Random-effects GLS regression                   Number of obs      =        65
Group variable: i                               Number of groups   =        13

R-sq:  within  = 0.0000                         Obs per group: min =         5
       between = 0.0000                                        avg =       5.0
       overall = 0.0676                                        max =         5

                                                Wald chi2(4)       =      9.35
corr(u_i, X)   = 0 (assumed)                    Prob > chi2        =    0.0528
```

roe	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
d1	-8.463077	5.16808	-1.64	0.102	-18.59233	1.666173
d2	-9.75	5.16808	-1.89	0.059	-19.87925	.3792496
d3	1.406154	5.16808	0.27	0.786	-8.723096	11.5354
d4	1.593846	5.16808	0.31	0.758	-8.535404	11.7231
d5	0	(omitted)				
_cons	12.23615	5.35811	2.28	0.022	1.734451	22.73786
sigma_u	14.128435					
sigma_e	13.176069					
rho	.53483706	(fraction of variance due to u_i)				

identify the effect of credit risk modeling on the efficiency of conventional banks in Pakistan along with examining the usage of credit risk models in the commercial banks of Pakistan. Thirteen banks were selected for the study consisting of a sample of 62% of the analysis unit. Data were collected from the published annual financial reports of the banks selected for the study. Frequency analysis was used to examine the usage of credit risk models in

Table 11 : Pearson Correlation Analysis of variables for Return on Asset (ROA)

	ROA	***PD Model***	***LGD Model***	***EAD Model***
ROA	1			
PD Model	0.391633	1		
LGD Model	0.358598	0.905232	1	
EAD Model	0.358598	0.905232	1	1

Table 12 : Pearson Correlation Analysis of variables for Return on Equity (ROE)

	ROE	***PD Model***	***LGD Model***	***EAD Model***
ROE	1			
PD Model	0.12879	1		
LGD Model	0.110628	0.905232	1	
EAD Model	0.110628	0.905232	1	1

the conventional banks of Pakistan. Descriptive analysis was used to describe the basic features of the data. Random effect model was used to estimate the relationship among variables. Pearson *R* correlation was computed to measure the strength of relationship between independent variables and dependent variables.

Frequency Analysis for examining the usage of Credit Risk Models:

Frequency analysis was used to examine the usage of credit risk models in the conventional banks of Pakistan. It was observed that there is only a Standard Chartered Bank which has been using the credit risk models since 2012. The MCB Bank has recently deployed the Probability of default (PD) model in year 2016.

The table depicted that out of 65 observations there were only 6 observations wherein the banks were found using the PD model for measuring the probability of default of their obligors. The percentile of not using the PD Model was 90.8% whereas the percentile of using the PD model was 9.2%. The results revealed that the PD models were not widely used in the banking industry of Pakistan.

Above is the graphical representation of the frequency of using the PD models in the banking industry of Pakistan. A small slice of the whole pie chart is representing the banks using PD models for measuring the probability of default of their obligors.

The table depicted that out of 65 observations there were only 5 observations wherein the banks were found using the LGD model for measuring the loss given default. The percentile of not using the LGD Model was 92.3% whereas the percentile of using the LGD model was 7.7%. The results revealed that the LGD models were not widely used in the banking industry of Pakistan.

Above is the graphical representation of the frequency of using the LGD models in the banking industry of Pakistan. A small slice of the whole pie chart is representing the banks using LGD models for measuring the loss given default.

The table depicted that out of 65 observations there were only 5 observations wherein the banks were found using the EAD model for measuring the exposure at default. The percentile of not using the EAD Model was 92.3% whereas the percentile of using the EAD model was 7.7%. The results revealed that the EAD models were not widely used in the banking industry of Pakistan.

Above is the graphical representation of the frequency of using the EAD models in the banking industry of Pakistan. A small slice of the whole pie chart is representing the banks using EAD models for measuring the exposure at default.

The table revealed that the banks in Pakistan were not using the credit risk models except a very few. There was only a Standard Chartered Bank which has been using the credit risk models since 2012. The MCB Bank also took the initiative and deployed the PD model in year 2016 for rating the obligors on probability of default.

Below is the graphical representation of the aforementioned findings.

The results have shown that there was only one bank which has been using the PD model since 2012. The MCB Bank was found among the followers by deploying the PD model in year 2016.

The results have shown that there was only a single bank which has been using the LGD model since 2012. It was revealed from the study that banks in Pakistan are

Table 13 : Pearson Correlation Analysis of variables for Return on Equity (ROE) & Return on Asset (ROA)

		PD Model	LGD Model	EAD Model	ROE	ROA
PD Model	Pearson Correlation	1				
LGD Model	Pearson Correlation	.905	1			
EAD Model	Pearson Correlation	.905	1.000	1		
ROE	Pearson Correlation	.129	.111	.111	1	
ROA	Pearson Correlation	.392	.359	.359	.812	1

not using the credit risk models for measuring the credit risk.

Below is the graphical representation of the aforementioned findings.

The trends observed in the use of EAD model were not found very different from the LGD model. The results revealed that there was only a one banks using the EAD model since 2012.

Below is the graphical representation of the aforementioned findings.

Descriptive Analysis:

Descriptive analysis was applied on all variables to describe the basic features of their data.

The descriptive analysis is used to describe the basic features of data. The table depicted that the number of observations considered for the study was 65. PD model was having a mean of 0.0923 with a minimum and maximum of 0 and 1 respectively which shown that the PD model was not commonly in the use of banks. Standard deviation of PD model was 0.29171. Both LGD model and EAD model were having the mean of 0.0769 with the range of 0 to 1 and standard deviation of 0.26854. PD model, LGD model and EAD model were the categorical variable indicating '0' as not using the model and '1'as holding the model. Mean of ROE was 19.372 with the range of -94.34 to 29.96 as maximum. The range of ROE was very wide indicating that there are many other factors influencing on ROE. Standard deviation of ROE was 19.37 indicating the large variation in sample data. ROA was observed having the mean of 0.9014 with the minimum '-2.03' and maximum '2.94'. Standard deviation of 1.070 was found for ROA.

Panel Least Square Regression Analysis (Random Effects Model):

Regression analysis is a statistical process for estimating the relationship among variables. Random effects model was used to analyze the impact of variables. The random effects model assumes that variation across the entities is random and uncorrelated with the independent variable selected for the study.

The results of this analysis revealed that the credit risk models have an effect on return on asset of banks. The null hypothesis was accepted since the value of chi square was less than 0.05. R Squared was 0.0358 indicating the proportion of the variation in dependent variable explained by the independent variables. Confidence interval was set at 95%. Two tail 'p' value tests the hypothesis that each coefficient is differed from zero and to reject this p value has to be lower than the 0.05. Keeping in consideration the underlying rationale, it was observed that the significant relationship exists between dependent and independent variables as the value of p was above 0.05. The calculated value of 'Z' was also found less than the tabulated value of 'Z' at 5% significance level except in one instance.

The results of this analysis revealed that the credit risk models have an effect on the ROE of banks. The null hypothesis was accepted since the value of chi square was equal to 0.05. R Squared was 0.0676 indicating the proportion of the variation in dependent variable explained by the independent variables. Confidence interval was set at 95%. Two tail 'p' value tests the hypothesis that each coefficient is differed from zero and to reject this p value has to be lower than the 0.05. Keeping in consideration the underlying rationale, it was observed that the significant relationship exists between dependent and independent variables as the value of p was above 0.05. The calculated value of 'Z' was also found less than the tabulated value of 'Z' at 5% significance level which led to the acceptance of null hypothesis.

Pearson Correlation Coefficient Analysis:

Pearson correlation measures the strength of a relationship between two variables. In other words, we may say that it measures how strongly the variation in one variable is correlated with the change in second variable. Its value ranges from -1 < 0 < 1 wherein -1 implies that there is a perfect negative relationship between predictor and criterion, 1 implies that there is a perfect positive relationship between predictor and criterion and 0 implies that there is no relationship between predictor and criterion.

The results established that all three models were having a moderate correlation with Return on Asset (ROA). Positive moderate relationship was found between Credit risk models and ROA which means that with the usage of credit risk models, the return on asset will be increased. A perfect positive correlation was found among PD Model, LGD Model, and EAD Model whereas moderate positive relationship was found between all three models and ROA, detailed as following; correlation between PD and ROA was 0.392, between LGD and ROA was 0.359, and between EAD and ROA was 0.359.

The results indicated that all three models were having a weak correlation with the Return on equity (ROE). Positive weak relationship was found between Credit risk models and ROE which means that with the usage of credit risk models, the return on equity will be increased but not considerably. A perfect positive correlation was found among PD Model, LGD Model, and EAD Model whereas weak positive relationship was found between all three models and ROA, detailed as following; correlation between PD and ROE was 0.129, between LGD and ROE was 0.111, and between EAD and ROE was 0.111.

The above table provided a quick summary of Pearson 'R' correlation analysis of all variables determining how strongly the variation in one variable was correlated with the change in second variable. The results revealed that the all three models were having a moderate correlation with Return on Asset (ROA) and a weak relationship with Return on Equity (ROE). Positive moderate relationship was found between Credit risk models and ROA which means that with the usage of credit risk models, the return on asset will be increased. A perfect positive correlation was found among PD Model, LGD Model, and EAD Model whereas moderate positive relationship was found between all three models and ROA, detailed as following; correlation between PD Model and ROA was 0.392, between LGD Model and ROA was 0.359, and between EAD Model and ROA was 0.359. A weak positive relationship was found between all three models and ROE as detailed following: correlation between ROE and PD model was 0.129, correlation between ROE and LGD model was 0.111, and correlation between ROE and EAD model was 0.111. The results revealed that ROE will be improved with the usage of credit risk models but the strength of relationship was weak.

SUMMARY, CONCLUSIONS AND IMPLICATIONS

Summary:

The objective of this study was to examine the usage of credit risk models in the conventional banks of Pakistan and to identify the effect of credit risk modelling on the efficiency of banks. Credit risk models are used to measure and manage the credit risk taking into account the correlations in credit quality between different borrowers by considering the fact that they may operate in the same industries and / or countries and be influenced by the same economic forces. There are three key parameters of credit risk modelling which are probability of default, loss given default, and exposure at default. The independent variables identified for the study were PD Model, LGD Model and EAD Model whereas ROA and ROE were taken as the measure of bank's efficiency. Thirteen banks were selected in a sample to undertake this research study. Data were ranging from year 2012 to 2016. Data set was consisting of 65 observations. Data were collected from the published annual financial reports of the commercial banks. Different kinds of tests were applied depending upon the nature of data and objectives of the study. Frequency analysis was applied to examine the usage of credit risk models. On the basis of hausman test, the random effects model was used to determine the relationship between predictor and criterion. Pearson correlation analysis was applied to examine the strength of relationship. Descriptive analysis was also applied on the data. The results of this study revealed that the banking industry of Pakistan was not enough advanced in terms of adopting the credit risk models. Another key finding derived from the results that the credit risk models have an effect on the efficiency of banks. The Pearson correlation analysis shown that the moderate positive relationship exists between predictors and ROA whereas; weak positive relationship has been found between predictors and ROE.

Findings

The main findings of this research study are summarized below to have an overview of the situation.

First objective of this research study was to examine the usage of credit risk models by the conventional banks in Pakistan. The frequency analysis was applied to examine the situation. The results of the analysis have shown that only 9% of the total dataset were using the PD model. If we see it in numbers then there were only 6 observations wherein banks were found using the PD model. There were only 7.7% of the total dataset which were using the LGD Model and EAD Model. We may say in reference to $Ho_1, Ho_2,$ and Ho_3 that there is an existence of credit risk models in Pakistan but the existence is not significant and considerable.

The descriptive analysis was applied to describe the basic features of the data. PD model was found with the mean of 0.0923 ranging from 0 to 1. LGD & EAD models were found with the mean of 0.0769 ranging from 0 to 1. ROE was with the mean of 9.1935 ranging from -94.34 to 29.96. ROA was with the mean of 0.9014 ranging from -2.03 to 2.94.

The random effects model was applied to estimate the relationship between predictors and criterion. Relationship of predictors with ROA was found significant with chi square value of 0.0368. R Squared was 0.0358 indicating the proportion of the variation in dependent variable explained by the independent variables. The calculated value of 'Z' was also found less than the tabulated value of 'Z' at 5% significance level except in one instance. The relationship of predictors with ROE was also found significant with chi square value of 0.05. R squared value was 0.0676. Calculated value of Z was also found less than the tabulated value of Z.

Pearson correlation coefficient analysis was applied to estimate the strength of relationship between predictors and efficiency measures which are ROA and ROE. A moderate positive relationship was found between predictors and ROA. The correlation between PD and ROA was 0.392, between LGD and ROA was 0.359, and between EAD and ROA was 0.359. A positive weak relationship was found between predictors and ROE. The correlation between PD and ROE was 0.129, between LGD and ROE was 0.111, and between EAD and ROE was 0.111. Based on the results of analysis, we can say that the credit risk modelling has an effect on the efficiency of banks. Hence, all hypotheses from Ho_4 to Ho_{11} are accepted.

Conclusions

It is concluded from the study that credit risk models are not widely used by the commercial banks of Pakistan. In fact there is only one bank which has been using the credit risk models since 2012. One more bank took the initiative and deployed the PD model in year 2016. The results of this study revealed that the predictors have a power to estimate the relationship among variables. In other words, we may say that the credit risk models have an effect on the efficiency of banks, measured through ROA and ROE. A moderate positive relationship was found between credit risk models and ROA whereas, a weak positive relationship was found between the predictors and ROE.

Recommendation

Following are the few recommendations:

- Credit risk models are generally used in financial institutions for evaluating the economic capital necessary to face the risk associated with their credit portfolio. It is recommended to the management of all commercial banks to develop and deploy the credit risk models in their banks.
- It is recommended to the management of all commercial banks and State Bank of Pakistan to hold the training sessions and seminars for creating the awareness among bankers for credit risk modelling.
- It is recommended to the researchers to work in this area of interest as a very limited research work has been found in this area of study especially from Pakistan.

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