Credit Risk Models for Managing Bank's Agricultural Loan Portfolio

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12 October 2007

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October 12, 2007

Abstract

In this paper, we have developed a credit scoring model for agricultural loan portfolio of a large Public Sector Bank in India and suggest how such model would help the Bank to mitigate risk in Agricultural lending. The logistic model developed in this study reflects major risk characteristics of Indian agricultural sector, loans and borrowers and designed to be consistent with Basel II, including consideration given to forecasting accuracy and model applicability. In this study, we have shown how agricultural exposures are typically can be managed on a portfolio basis which will not only enable the bank to diversify the risk and optimize the profit in the business, but also will strengthen banker-borrower relationship and enables the bank to expand its reach to farmers because of transparency in loan decision making process.

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The author would like to thank Dr. Asish Saha (Director, NIBM), Dr. K Ramesha, Dr. A U Gadewar for extremely helpful comments and suggestions. The author is also thankful to Mr. N Narasa Reddy for all his help.

1. Introduction

The structure and conduct of agricultural lending has been changing rather dramatically over the past two decades. Some of the forces causing change have been occurring at the farm level, where farmers and ranchers are changing the way they do business. Other changes have been occurring in global markets for agricultural and value added food and fiber products. Rapidly changing dynamics are occurring in technology embodied in inputs and management of resources and the environment. Finally, evolution is occurring in the credit market serving agriculture and the regulations that govern institutional behavior.

With this changing face of agricultural lending, the agricultural lending decision making process is becoming much more complex as a result of contractual and ownership arrangement issues, locational issues, and management quality and risk management issues. The Farm Credit System, with its unique structure, faces a number of issues as it attempts to maintain its competitive position in light of the evolving farm customer base and activities of competitors providing loans and services in this market. The degree of competition in agricultural lending will influence quantity and quality of loans made.

There are a number of forces that will drive further change in agricultural lending in the next few years. These drivers in turn will influence credit analyses and portfolio management decisions at agricultural lending institutions. Banks will likely see several changes that will affect agricultural lending. This includes the potential de-emphasis on commodity safety nets (loan deficiency payments and countercyclical payments) as well as direct payments and increased emphasis on revenue insurance for a broad range of crop and livestock commodities. Continued programs may involve payment limitations and needs testing. Other policy-related drivers include issues related to water rights, zoning, and other regulations dealing with odor, dust, chemicals, and noise in agricultural production. Finally, macroeconomic policies affecting the general economic health of the domestic and global economies will also affect farm profit margins and debt repayment capacity.

The Basel II Capital Accords, scheduled to be implemented by the end of 2009, has implications for setting capital requirements, supervisory review, and market discipline at banking institutions. The measurement and management of credit risk, operational risk, and market risk lie at the heart of Basel II. While implementation will begin at the nation's largest banks, the more advanced approaches to calculating capital requirements and other management practices will have implications for other banks and non-bank lending institutions as well.

With the many forces changing the face of agricultural lending, this is a good time to examine shifting paradigms impacting agricultural lending as it evolves over the next 15 years from both the customer side of the market as well as from the lender perspective.

The New Basel Accord does not include any special treatment for agricultural lending. Basel II implies that large agricultural loans would be treated as corporate loans and small agricultural loans as retail loans. The regulators, however, need to take into account the particular characteristics of farm loans when setting capital charges for organizations involved in agricultural lending (Barry, 2001). Farm businesses are characterized by cyclical performance, seasonal production patterns, high capital intensity, leasing of farmland, participation in government programs, and annual payments of real estate loans. Because of these characteristics, losses in agricultural lending may not be frequent, but could be large due to high correlations among farm performances. At the same time, high capital intensity, especially involving farmland, offers relatively strong collateral positions, thus mitigating the severity of default when default problems do arise.

Katchova and Barry (2005) developed models for quantifying credit risk in agricultural lending. They calculated probabilities of default, loss given default, portfolio risk, and correlations using data from farm businesses. The authors showed that the calculated expected and unexpected losses under Basel II critically depend on the credit quality of the loan portfolio and the correlations among farm performances. These analyses of portfolio credit risk could be further enhanced if segmented by primary commodity and geographical location. Agricultural lenders could adopt similar models to quantify credit risk, a key component in the calibration of minimum capital requirements.

A credit risk model suitable for agricultural loan is developed based on the sample data obtained from a large Indian Public Sector Bank. The model incorporates basic characteristics of the borrowers and various risk parameters that significantly influence the borrower's creditworthiness. Such model would enable the bank to identify key risk parameters in agricultural loan that would help the lending officers to take decisions and manage the loan portfolio in a better way to minimize credit losses.

The New Basel Capital Accord (Basel II) provides added emphasis to the development of portfolio credit risk models. An important regulatory change in Basel II is the differentiated treatment in measuring capital requirements for the corporate exposures and retail exposures. Basel II allows agricultural loans to be categorized and treated as the retail exposures. However, portfolio credit risk model for agricultural loans is still in their infancy. Most portfolio credit risk models being used have been developed for corporate exposures, and are not generally applicable to agricultural loan portfolio. The objective of this study is to develop a credit risk model for agricultural loan portfolios. The model developed in this study reflects characteristics of the agricultural sector, loans and borrowers and designed to be consistent with Basel II, including consideration given to forecasting accuracy and model applicability. This study conceptualizes a theory of loan default for farm borrowers. A theoretical model is developed based on the default theory with several assumptions to simplify the model

When modeling credit risk for agricultural loans, one must account for the attributes of agricultural sector and its borrowers. The performance of the sector is also influenced by economic cycles and is highly correlated with farm typology, commodity, and geographical location. Credit risk for agricultural loans is closely related to a farm's net cash flows like other retail loan categories. However, these cash flows exhibit annual cycles. Banks catering to agriculture sector need a unique credit risk model for their loan portfolio that captures these and other characteristics unique to agriculture.

For individual farmers and agribusinesses, risk management involves choosing among alternatives for reducing the effects of risk on the firm, thereby affecting the firm's welfare position. Risk management often requires the evaluation of tradeoffs between changes in risk, expected returns, entrepreneurial freedom, and other factors. Research on risk management issues in agriculture has been among the main topics of interest of the Regional Research Committee for Financing Agriculture in a Changing Environment: Macro, Market, Policy, and Management Issues,

A credit rating is a summary indicator of risk for banks' individual credit Exposures. Traditionally, most financial institutions relied virtually exclusively on subjective analysis or the so-called banker expert system to assess the credit risk of borrowers. Bank loan officers used information on various borrower characteristics, which are called as the "5 Cs" of credit. They are (1) character of borrower (reputation), (2) capital (leverage), (3) capacity (volatility of earnings), (4) collateral, and (5) condition (macroeconomic cycle). However, this method may be inconsistent if it risk weights are also based on expert's opinion. The weights should be grounded based on the historical experiences. Accordingly, we have followed a statistical model approach which takes care of "5 Cs" subjectively and produce consistent forecast about the borrower's default probability. Bank can use such credit rating tool in the loan processing, credit monitoring, loan pricing, management decision-making, and in calculating inputs (Probability of default, loss given default, default correlation and risk contribution etc. which has been discussed in later section in detail) for portfolio credit risk model.

The objective of this empirical research is to develop a credit risk model for an agricultural loan portfolio in India. This model takes into account the characteristics of the agricultural sector, attributes of agricultural loans and borrowers, and restrictions faced by commercial banks. The proposed model is also consistent with Basel II, including consideration given to forecasting accuracy and applicability. We also suggest how such model would help the Indian Banks to mitigate risk in Agricultural lending.

2. Research Methodology

When modeling portfolio credit risk for agricultural loans, one must account for the attributes of the agricultural sector and its borrowers, which is substantially different from the other retail exposures. It experiences chronic cash flow pressures resulting from relatively low but volatile returns to production assets. These characteristics contribute to the aggregate debt-servicing capacity and credit worthiness during downward swings in farm income and reductions in asset value, as happened in 1980s (Barry et al., 2002). Credit risk in agricultural loans is closely tied to a farm's net cash flow just as it is for other retail loan categories. Expected net cash flows are a good leading indicator for the eventual credit worthiness of an agricultural borrower. This is dependent upon cropping pattern, crop yield, balance sheet position of the borrower and local situational factors.

Volatile performance of farm businesses stems mainly from fluctuating commodity prices and weather conditions, which are highly correlated, especially for farms with similar typology, commodity, and geographical region (Bliss, 2002). This phenomenon implies that segmentation of an agricultural loan portfolio should consider commodity and regional differences. Economic performance in the agricultural sector is also widely influenced by events in both the domestic and international economy. Capturing the state of these economies is critical in credit risk modeling for agricultural sector. That is why the country is divided into approximately 126 agro-climatic zones based on weather, soil type etc. To better capture the impact of state of economies, one has to have a robust model in the bank that captures these variations. This can be done by analyzing the entire portfolio of the bank which is diversified across various agro-climatic regions.

Net cash flows in the agricultural sector typically exhibit cycles within the year. However, term debt repayment is typically annual in nature. These characteristics restrict more frequent periodicity in model specification. In addition, monthly and quarterly data is difficult to obtain. When a bank chooses a model among several candidates, applicability of the model becomes one of the essential considerations since data availability, authenticity of data is more problematic in agricultural sector. However, in this research study, we have made an attempt to study the crucial factors that assumed to play important role in credit risk of agricultural loan of a Bank.

The credit risk is defined by the risk of default which has been taken as the dependent variable in our model. There have been various arguments about the definition of default. They vary by models and by banks, and depend on the philosophy and/or data available to each model builder. Liquidation, bankruptcy filing, loan loss (or charge off), non-performing loan, or loan delayed in payment obligation are used at many banks as proxies of loan default. In our study, we have taken Non Performing Assets of the bank as defaulted loans. According to Reserve Bank of India (RBI) definition of NPA, if the interest and/or installment of principals remains overdue for two harvest seasons but for a period not exceeding two and half years in the case of an advance granted for agricultural purpose (new definition circulated by RBI from March 31, 2001). Accordingly, NPA, Substandard assets, doubtful assets and loss assets are categorized into defaulted assets. Based on a sample data of 800 accounts from four circles, we try to find out the major characteristics that decide the nature of risk in agricultural loan. After finding out these parameters, we try to develop a credit scoring model for the agricultural loan portfolio that would help the bank to assess risk in such loan segment and manage the risk systematically in these zones.

2.1. Score Card Building for Agricultural Loans (Critical Steps):

- Define Agricultural products (Facility Types)
- Create sub-populations of Agri-Loan portfolios (across circles/regions)
- Specify the objective and performance definition (here, performance criteria is defaulted facility/standard accounts)

- Design analysis sample - a sufficient, random, representative portion of recent accounts with known payment behavior, plus declined and or bad applications for each sub-population. Here we have received 900 borrower data from the bank over the period: 1992 to 2007. However, due to lot of missing information, we had to reduce the sample into 800 accounts. While editing/filtering the data, we noticed lot of missing information which would have been valuable in our analysis. Hence we had to reduce the sample to 800 accounts.

2.2. The Agri-Score Card Development Process:

- Feasibility study
- Sample definition
- Data assembly
- Analysis of characteristics
- Reject inference
- Scorecard build
- Risk Differentiation
- Validation (on the basis of bank's internal data)
- Strategy selection and documentation
- Implementation

2.3. Relevant Variables that have been identified as predictor of default risk in Agricultural Loan:

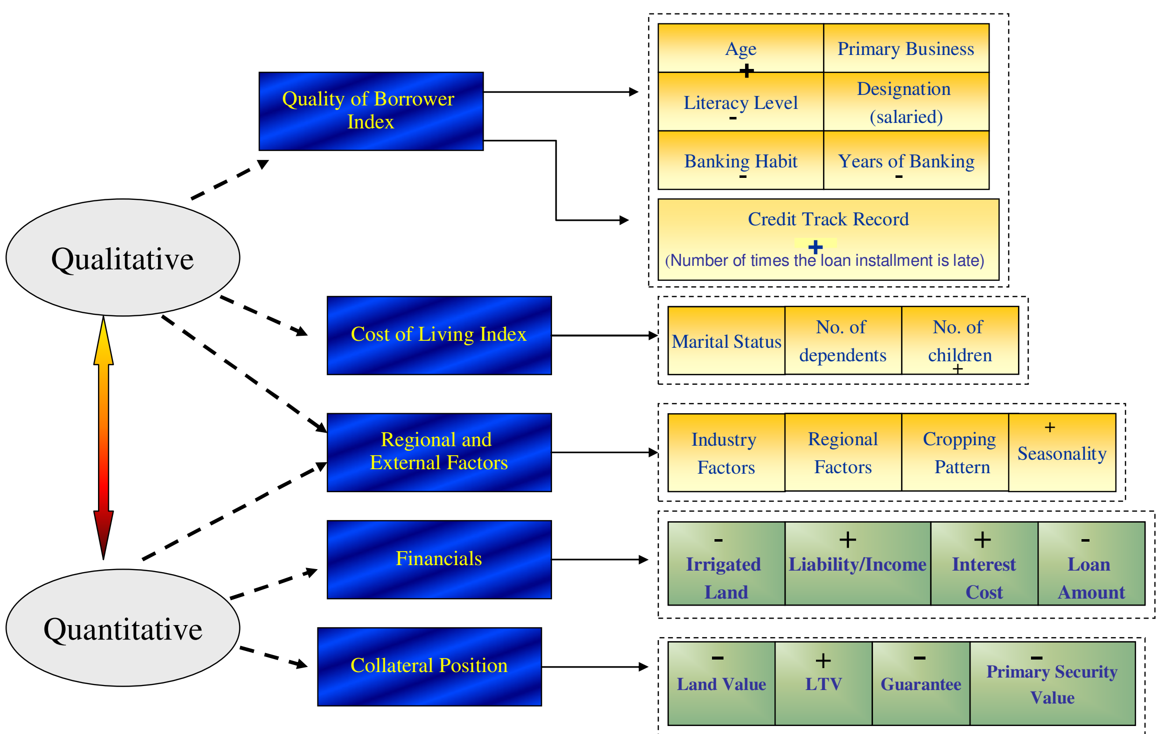

Figure1: Risk Parameters of Agriculture Rating Model

We had asked for as many as 63 data fields from the bank and based on our hypothesis, these fields have been classified into two major categories: qualitative and quantitative factors. Again in each category we generally look at Borrower characteristics by categorizing them into Quality of Borrower Index and Cost of Living Index, and then we group them into Regional and External Factors, Financial Factors and Finally Collateral Position. These are the major risk categories that have been used in our "Credit Scoring Model" for the Public Sector Bank. The sign of the factors shows the relationship between these factors with the default probability. For example, "LTV", which is ratio of the amount loan outstanding over value of the security, is positively related to default risk. It means, higher is the ratio, lesser is the proportion of collateral attached to the loan, and higher is the probability that the loan would default. Similarly, higher is the value of the land; lower is the chance of risk as indicated by the negative sign. In summary, Figure 1 documents the important risk parameters that a credit officer must look at objectively before sanctioning an Agriculture loan proposal and weight these factors to rate the Agri-borrower. For weighting these factors, they may use the following Table (Table 1) that depicts the actual contribution of these factors on the creditworthiness of the borrowers.

3. Empirical Results:

Table1: Factors and their contributions to Default Risk in Agriculture Loan

Risk Parameters	Weights	Significance
QOB Index	**3.74%**	
Age (+)	0.09%	Yes*
Banking Habit (-)	3.48%	Yes*
Age of Relationship with Bank (-)	0.16%	Yes*
COL Index	**0.05%**	
Number of Dependents (+)	0.05%	No
Regional & External Factors	**34.57%**	
Crop Intensity (+)	1.37%	Yes***
Circle	14.24%	Yes
Crop Type	9.97%	Yes
Yield of Food Crop (-)	6.92%	Yes***
Yield of Cash Crop (-)	2.07%	No
Financials	**3.88%**	
Loan Size in Log Scale (-)	1.64%	Yes**
Total Liability/Total Income (+)	0.29%	No
Interest Burden (+)	1.96%	Yes***
Collateral Position	**51.80%**	
Facility Type	48.22%	Yes
Loan Tenure (-)	0.96%	Yes***
Presence of Guarantor (-)	1.92%	No
Primary Security Type	0.24%	No
Loan Amount/Primary Security Value (+)	0.01%	No
Value of Own Land/Land Area in Acres (-)	0.45%	No
Other Factors	**5.97%**	No
Total	**100.00%**	

One can see from Table 1 that Regional & External Factors and Collateral Position contribute more in assessing creditworthiness of the Agricultural loans. As far as other factors are concerned, the bank needs to look at the relevant documents submitted by the borrower, presence of government subsidy, market condition of the agricultural products (price movement, production etc.) as additional factors to closely monitor the risk profile of Agri-portfolio.

Table: 2	**Dependent Variable: ddef (this is a dummy and the value=1 if loan is bad and =0 if good)**				
Independent Variables	**short names**	**Coefficients**	**Std. Error**	**z values**	**P>|z|**
Natural Log(Loan Amount)	zloansize	-0.8566	0.3618	-2.3700	0.0180
Food Crop Area/Total Own Land Area	agriyldfd	-3.6213	1.4250	-2.5400	0.0110
Cash Crop Area/Total Own Land Area	agriyldcsh	-1.0843	1.2558	-0.8600	0.3880
Total Liability/Total Income	zliab_incr	0.1499	0.2814	0.5300	0.5940
Number of Dependents	nodepend	0.0253	0.1360	0.1900	0.8530
Age of the Borrower (in Years)	age	0.0494	0.0281	1.7500	0.0790
Loan Amount/Primary Security Value	zltvprm	-0.0029	0.0161	0.1800	0.8580
Primary Security Type[&]	prim_scd	0.1239	0.3884	0.3200	0.7500
Whether the Borrower has A/C in Bank	canbnkd	-1.8216	0.9426	-1.9300	0.0530
Years of Relationship with the Borrower[$]	age_reln	-0.0854	0.0500	-1.7100	0.0880
Tenure of the Loan	loan_ten	-0.5047	0.1902	-2.6500	0.0080
Interest Rate Charged on the Loan	interest	1.0247	0.2828	3.6200	0.0000
Cropping Intensity	crop_int	0.7175	0.2922	2.4600	0.0140
Value of own Land/Total Own Land Area	landvlr	-0.2339	0.2100	-1.1100	0.2650
Presence of Guarantor	guardum	-1.0048	0.8433	-1.1900	0.2330
Crop Type1 (Traditional)	cropdum1	3.8408	1.2717	3.0200	0.0030
Crop Type2 (Cash Crop)	cropdum2				
Crop Type3 (Other Type)	cropdum3	-0.2427	0.9182	-0.2600	0.7920
Crop Type4 (Horticulture)	cropdum4	1.1333	0.9074	1.2500	0.2120
Loan Type1 (KCC)	loantypdum1	-5.6681	14.0158	-0.4000	0.6860
Loan Type2 (KCC & Development)	loantypdum2				
Loan Type3 (Development)	loantypdum3	-2.3921	14.0120	-0.1700	0.8640
Loan Type4 (Farm Development)	loantypdum4	-3.9041	14.1185	-0.2800	0.7820
Loan Type5 (Tractor Loan)	loantypdum5	-1.8477	14.0293	-0.1300	0.8950
Loan Type6 (Vehicle Loan)	loantypdum6				
Loan Type7 (Crop Loan)	loantypdum7				
Loan Type8 (Crop Loan/Development Loan)	loantypdum8				
Loan Type9 (Farm House)	loantypdum9				
Loan Type10 (Farm Machinery)	loantypdum10	-4.3653	14.0895	-0.3100	0.7570
Loan Type11 (Investment)	loantypdum11	-4.1571	14.0925	-0.2900	0.7680
Loan Type12 (Minor Irrigation)	loantypdum12	-2.9085	14.0187	-0.2100	0.8360
Loan Type12 (Govt. Loan)	loantypdum13				
Circle1 (Bangalore)	circld1				
Circle2 (Hassan)	circld2	-1.6882	0.7949	-2.1200	0.0340
Circle3 (Hubli)	circld3	-2.1549	0.8775	-2.4600	0.0140
Circle4 (Mangalore)	circld4	-3.6126	1.8247	-1.9800	0.0480
Intercept (or Other Factors)	_cons	-3.1230	14.6943	-0.2100	0.8320

Notes:

1. Units are in Rs. Lac or in Acres, Others in Numbers
2. The Model overall goodness of fit: R^2=0.411; Chi^2 (28)=81.27*** and Number of estimated Observations: 448

& Three types of prime securities are taken, =1 if Hypothecation, =2 for Hypothecation and Fixed Assets, =3 for Fixed Assets. $ It means for how many years the borrower is dealing with the Bank

Table 2 reports the output of logistic regression exercise that we have done on the 800 borrower sample data. The dependent variable is a dummy “DDEF” which is coded =1 for defaulted assets and code=0 for standard assets. This is called “binary dependent variable”. The 36 independent variables used in the “logistic regression” analysis are listed in the first column of the above Table 2 and their short names are reported in column 2. Logistic Regression is a limited dependent variable regression that assumes logistically distributed error term and uses maximum likelihood function for estimating the coefficients (or weights) of the independent variables. These empirically derived weights or coefficients are reported in column 3 of the same table along with their sign. The standard error of coefficients and hence the z values (ratio of coefficients divided by standard errors) are reported in column 4 and 5 of the above table. The probabilities of significance are reported in the last column 6. If $P>|z|$ is less than 0.10, we have included them as significant variables and significance it below 10%. If $P>|z|$ is less than 0.05, the independent variables are referred as significant at 5% confidence level.

It is important to note that these factors reported in the above table have correlation between them and therefore have combined effect on the creditworthiness of the borrower. For example, “age” factor in isolation may not have direct bearing on the risk unless we also take into consideration the family size, land holding pattern, orientation towards farming. That is why, we have done a multivariate analysis of all these factors (quantitative as well as qualitative) on the risk of agricultural lending. In a We also have examined that risk profile of different age group (group1 ranges from 22-42 (contribute 25% of sample), group 2 from 43-62 (75%) and group 3 above 62 years (99%). In a separate regression, we have found that farmers/borrowers in 1^{st} age group (i.e. 22-42) are much safer than the other two groups in terms of default risk.

The overall explanatory power of the logistic scoring model is measured by R^2 and the fitness result shows that model’s fitness is good (with explanatory power of 41.1%). The Chi^2 goodness of fit test also confirms the same.

From the regression output, we obtain the formula for our logit scoring model:

Logit Z Score:

$$
\begin{aligned}
&-3.1230-0.8566\times(\text{zloansize})-3.6213\times(\text{agriyldfd})-1.0843\times(\text{agriyldcsh})+0.1499\times(\text{zliab\_incr})\\
&+0.0253\times(\text{nodepend})+0.0494\times(\text{Age})-0.0029\times(\text{zltvprm})+0.1239\times(\text{prim\_scd})-1.8216\times(\text{canbnkd})\\
&-0.0854\times(\text{age\_reln})-0.5047\times(\text{loan\_ten})+1.0247\times(\text{interest})+0.7175\times(\text{crop\_int})-0.2339\times(\text{landvlr})\\
&-1.0048\times(\text{guardum})+3.8408\times(\text{cropdum1})+0.00\times(\text{cropdum2})+0.2427\times(\text{cropdum3})\\
&+1.1333\times(\text{cropdum4})-5.6681\times(\text{loantypdum1})+0.00\times(\text{loantypdum2})-2.3921\times(\text{loantypdum3})\\
&-3.9041\times(\text{loantypdum4})-1.8477\times(\text{loantypdum5})+0.00\times(\text{loantypdum6})+0.00\times(\text{loantypdum7})\\
&+0.00\times(\text{loantypdum8})+0.00\times(\text{loantypdum9})-4.3653\times(\text{loantypdum10})-4.1571\times(\text{loantypdum11})\\
&-2.9085\times(\text{loantypdum12})+0.00\times(\text{circld1})-1.6882\times(\text{circld2})-2.1549\times(\text{circld3})-3.6126\times(\text{circld4})
\end{aligned}
$$

Using the above formula one would get the logit Z score for a loan if information on all the 37 parameters specified above is available. If certain parameter is missing, the logit Z score value would not give the correct picture about the credit worthiness of the borrower. Therefore, to ensure more correct prediction about the borrower’s health, it is advised to collect information about all the 36 parameters (since 37^{th} parameter is an intercept whose value is given).

After obtaining the score, following expression can be used for projecting Expected Probability of Default on the loan that would help the credit officer to classify the loan proposal into risk categories which would be the basis for making credit decisions.

Expected Probability of Default for the Loan (EPD) is:

EPD= {1/ (1+exp (-logit Z Score))} ×100%

"exp" is exponential function whose value is approximately: 2.718281828.

After EPD is obtained, the loan facility can be classified into following risk buckets through internal mapping (see Table 3). The internal mapping exercise is being done by comparing the model's predicted EPD (based on the logit score obtained) with the actual default rates are various percentiles. This calibration exercise for risk bucketing is done based on the within sample data of 800 accounts over the period 1992-2007 data obtained from the bank.

Table 3:

PD ranges (Fraction)	**Rating**	**Actual Default %**
0.00%-4%	R1	0.00%
4%-10%	R2	0.00%
10%-13%	R3	0.69%
13%-25%	R4	2.41%
25%-27.3%	R5	2.76%
27.3%-40%	R6	4.83%
40%-50%	R7	5.52%
50%-61%	R8 (Early Warning)	7.24%
61%-83%	R9 (Risky)	13.45%
83%-95%	R10 (Very Risky)	15.86%
95%-99%	R11 (Very Risky)	17.24%

3.1. Validation:

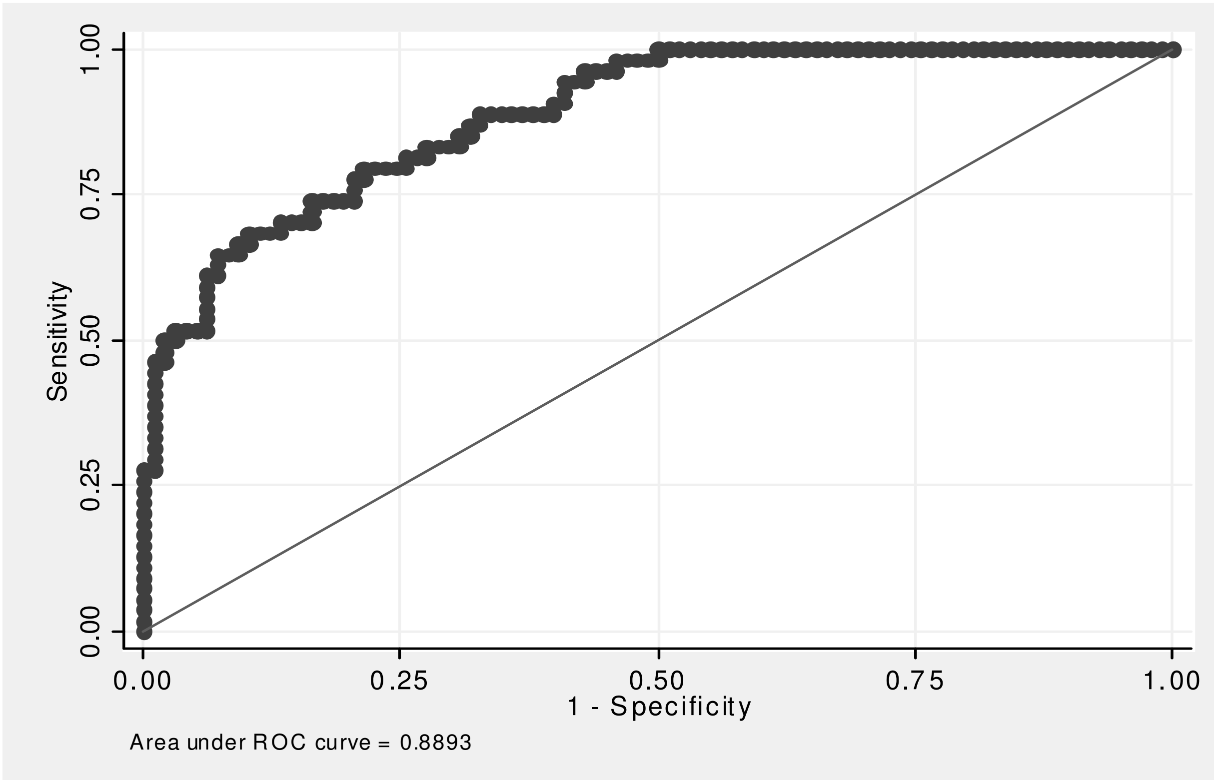

Figure 2: Receiver Operating Characteristic Curve measuring the discriminatory power of the model.

We have performed within sample validity of our Agri-credit scoring model. The above graph shows the proportion of defaulted loans vis-à-vis the proportion of solvent loans predicted by the logit z score model. The 45^0 diagonal line is a reference line which shows randomness in the prediction. Since the concave line is above the 45^0 line, it indicates that the model's classification power is good. That means if the predicted scores are ranked from bottom (high risk) to up (low risk) in an ascending order, the high range of scores (i.e., bottom portion of the above graph) is able to capture greater proportion of defaulted loans and upper portion (i.e. lower scores region) places more standard asset (low risk categories) in greater proportion. This way, model is able to discriminate between the good customer and bad customer. The discriminatory power is measured by the "Area under ROC curve" which is the area below the concave curve and it is 0.8893 which means it has ROC predictive power of 88.93% which is quite good.

3.2. Advantages of Agri-Credit Scoring Model:

The credit scoring model developed here based on the sample data would help the bank in the following way:

- Objectivity & quantitative assessment
- Improved (informed) decision making in a consistent manner
- Improved speed of loan processing as time and manual steps get reduced
- Improved customer service
- Cost efficiency - reduces loss rates while holding approval rates constant
- Allows for risk based pricing
- Improves approval rates while holding loss rates constant
- Reduces training time for new credit staff
- Sharpen/Improve analytical skills of credit officers
- It strengthens banker-borrower relationship because of transparency in loan decision making process

3.3. Further Benefits for the Bank:

- Finance is risk management, and scoring facilitates risk management
- Quantifies risk as the % chance that something 'bad' will happen
- Makes risk evaluation explicit, systematic, consistent (not just loan officer's 'gut feeling')
- Quantifies risk's links with characteristics
- Therefore, better risk management implies more loans with same effort, greater outreach, more market share, and greater profits
- Greatest benefit: *Strengthen the credit culture of explicit & conscious risk management*

3.4. Agriculture Risk Profile in the Bank under Study:

Table 4 and Table 5 portray the portfolio risk profile of the bank in Agriculture Loan segment. Table 4 shows that farm loan risk is relatively highest in Horticulture loans. As far as type of loans are concerned, Table 5 documents the fact that Kishan Credit Card Loans (KCC) have highest risk of defaults (38.62%) followed by Land Development loans (18.28%) and Farm Machinery loans (10%).

Table: 4

Year: 1992-07

SL. No.	Crop Type	Total N	Solvent N	Defaulted N	Relative Default %	Default %_to_Total
1	Traditional	115	55	60	21%	7.50%
2	Cash Crop	190	120	70	24%	8.75%
3	Mix/Others	105	78	27	9%	3.38%
4	Horticulture	327	223	104	36%	13.00%
5	Other Missing Categories	63	34	29	10%	3.63%
	Total	800	510	290	100%	

Table: 5

Year: 1992-2007

SL. No.	Loan Type	Total N	Solvent N	Defaulted N	Relative Default %	Default %_to_Total
1	KCC	328	216	112	38.62%	14.00%
2	KCC & Development	20	20	0	0.00%	0.00%
3	Land Development	115	62	53	18.28%	6.63%
4	Farm Development	47	37	10	3.45%	1.25%
5	Tractor Loan	48	35	13	4.48%	1.63%
6	Vehicle Loan	36	27	9	3.10%	1.13%
7	Crop Loan	28	7	21	7.24%	2.63%
8	Crop Loan/Development Loan	7	1	6	2.07%	0.75%
9	Farm House	3	3	0	0.00%	0.00%
10	Farm Machinery	81	52	29	10.00%	3.63%
11	Investment	17	8	9	3.10%	1.13%
12	Minor Irrigation	52	36	16	5.52%	2.00%
13	Govt. Loan	3	0	3	1.03%	0.38%
14	Missing Categories	15	6	9	3.10%	1.13%
	Total	800	510	290	100.00%	

One may argue that separate regression exercise to be carried out to find out the risk characteristics of each loan. However, logit Z score equation and the regression results reported in Table 2 take care of this problem. As already being discussed that each loan character is captured by the respective dummies that have been reported in the table. Hence, if anybody is interested to see the risk in a particular facility or crop or region, he has to refer the specific code being given for each type (or call dummies) and will get the predicted score and risk factors accordingly. It is obvious that all risk factors may not be equally important for all types of loans or crops. That is why we have considered crop-wise, loan wise control dummies to capture those effects and therefore our credit score model is robust.

3.4.1. Circle wise Default:

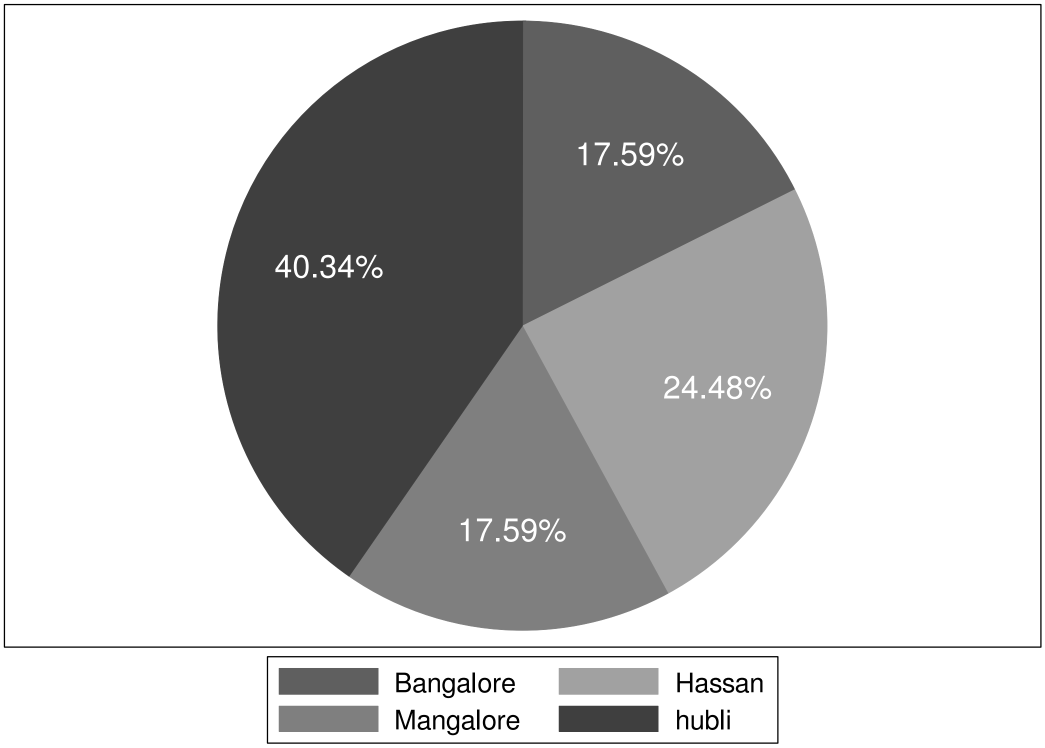

Figure 3: Pie Chart depicting Risk Profile of Circles

[Total number of defaulted loans=290]

Figure 3 gives a region-wise risk position of the portfolio. The hubli circle has the maximum (40.34%) contribution to total risk in Agricultural Loan of this State. The next risky circle is Hassan (24.48%) followed by Mangalore and Bangalore (17.59% each). It will guide the management to understand the risk concentration in various regions.

3.4.2. Crop-wise default:

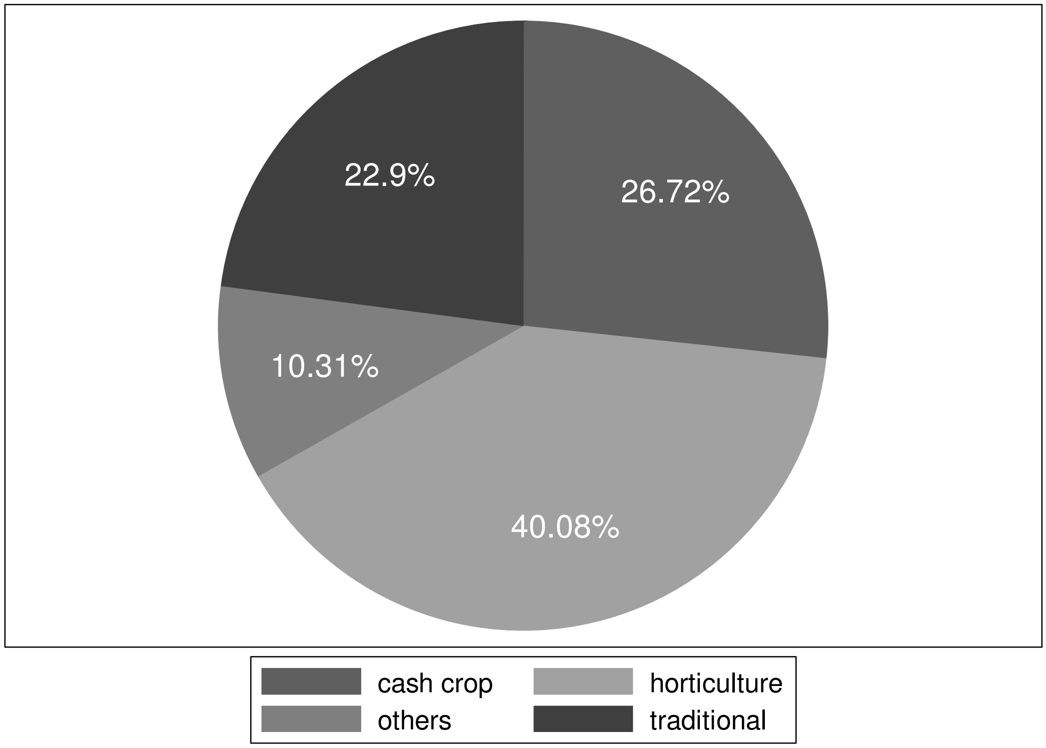

Figure 4: Pie-Chart depicting Risk Profile of Crops

Figure 4 portrays the crop wise portfolio risk composition. One can see that most of the defaulted loans are from horticulture (40.08%) followed by traditional crops (26.725). and cash crop items (22.9%). Others mean not classified (meager 10.31%) due to non-availability of information.

4. Recommendations

Portfolio Management of Credit Risk in Agriculture Lending

To systematically assess credit risk in Agricultural Lending, bank should look for a portfolio approach of managing the credit risk. This will allow the management to quantify the concentration risk across various dimensions and rationally suggest for diversification benefits. For portfolio assessment of risk, Bank has to calculate expected loss of agriculture portfolio as a whole:

Probability of Loan Loss: $EL=PD\times E\times LGD$
$UL=E\times LGD\times PD\times(1-PD)$
EL_P=sum of individual EL
UL_P=Sum of the risk contributions of individual loans.
Risk Capital measure by Value at Risk (VaR) =Maximum Loan Loss-Expected Loss

The maximum probable loss is the point in the tail of the loss distribution (as shown in Figure 5 below) where there is a "very low" probability that losses will exceed that point. The "Very low" probability is chosen to match the bank's desired credit rating. For example, a single-A-rated bank would require that there should be only 10 basis points of probability in the tail (i.e., 99.9% of confidence level that maximum loss will be covered by capital and bank will be able to maintain solvency with 0.10% probability), whereas AAA banks require around 1 basis point (i.e. 0.01% probability of solvency).

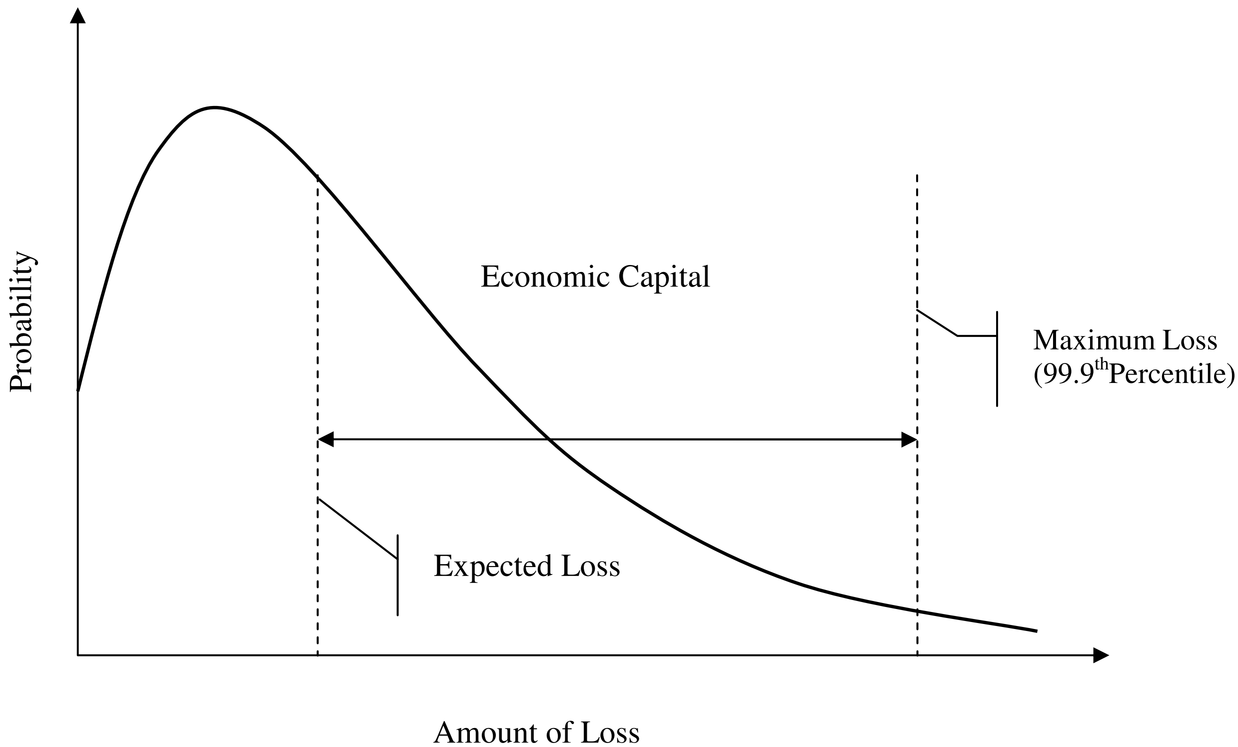

Figure 5: Measure of Value at Risk on Loss Distribution

For portfolio risk measure, bank has to first estimate the pooled probability of default on Retail-Agriculture loan. This pooled PD can either be obtained by counting rating wise default numbers of by generating a pool and count the default numbers like we have done in Table 4 and 5.

Similarly, they have to estimate the Loss Given Default (LGD) from the historical recovery experience on different loans over period or from their facility-wise LGD rating model (one has to develop for the bank from the internal data but it is possible). For example, LGD rating 1 (best grade) can be assigned to loans guaranteed by government agencies and to loans protected by good collateral. Similarly, loans with collateral-to-loan values (or primary security values) over 150% can also be included in this category. For rating 1, anticipated LGD (which is 100%-recovery rate) can be 10% (i.e. 90% recovery rate). An LGD rating of 2 can be assigned to loans with collateral-to-loan values between

100%-150% (expected LGD=20%-40%). Leased assets also can be included. An LGD rating of 3 can be assigned to loans with collateral-to-loan values between 50%-100% (expected LGD=50%-60%). An LGD rating of 4 can be assigned to unsecured loans and loans with collateral-to-loan values below 50% (expected LGD is more than 75%). The lowest LGD grade 5 can be given for Clean Loans/Totally Unsecured Loans which are very risky in nature (almost 100% LGD). Pooled/Composite rating can be obtained by combining borrower rating and facility rating. From borrower rating, one has to obtain PD for each rating grade which can be estimated by tracking rating transitions. Multiply that PD with the corresponding facility rating for the borrower. If borrower has taken many facilities, obtain average LGD rating (you may re-allocate the collateral in such case in multiple facilities are taken). After multiplying PD with anticipated LGD, you will get Expected Loss % (EL%). Now in terms of EL% rank the borrowers from lowest EL to highest EL. Suppose you have 10 rankings, the lowest will receive the best grade (grade 1) and worst (with highest EL%) will receive the lowest rating (10). This is just an illustration of the possible method for finding a combined rating for the agriculture sector.

Further, by counting joint movements of accounts to default categories over years, default correlation can be obtained which would enable the bank to estimate its portfolio unexpected loss and risk contributions and finally the "economic capital". In the case of geographically (region wise/state wise/branch wise) or product wise (say crop loan, tractor loan, development loan, horticulture, plantation etc.) dispersed agricultural retail portfolios, banks can estimate correlations using actual defaulted data, which is usually available in the internal system. The prime objective of economic capital measurement is to support strategic decisions. Economic capital attempts to measure credit risk in agricultural portfolio and provide a risk-adjusted common currency of risk so that bank can compare the risk adjusted profitability of its business across regions/branches and see more clearly which are the most deserving of further investment. Where the economic capital numbers are robust, they can be applied to tactical and competitive decisions. Thus, the bank can use economic-capital-based analysis to explore the profitability of their portfolios in terms of credit score.

5. Summary Conclusions

This section presents the credit scoring model for Agricultural loan that we have developed based on the sample data obtained from the Bank. After giving an overview of the key issues in credit risk management of agricultural loans, we talk about major risk drivers and their importance in assessing the creditworthiness of the borrowers. Since banks are firms balancing risk and return characteristics among alternative opportunities, banks cannot avoid risks. Credit risk is the largest risk faced by banks even in Agricultural loans. The most important implication of this chapter is the argument that agricultural exposures are typically can be managed on a portfolio basis, and many exposures in the same portfolio have similar risk characteristics. This will enable the bank to diversify the risk and optimize the profit in the business which will ultimately enable them to comply for the Basel II requirements under the advanced approach. In this direction, we have also suggested how to use this scoring model for portfolio management of risk. It is important to note that: entire exercise is based on a sample data. In order to have a robust model and robust tool for mitigating risk in agricultural loan which is perused as risky, for the entire bank, one has to enlarge the data sample and include other regions into the analysis. All these can be done in a separate assignment. However, as a pilot study, we have tried to demonstrate how this exercise can be done and it's utility to explore and expand the scope for further research.

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