Credit Risk Models for Managing Bank's Agricultural Loan Portfolio

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This paper develops a credit scoring model for agricultural loan portfolio of a large public sector bank in India and suggests how such a model would help the bank to mitigate risk in agricultural lending. The logistic model developed in this study captures the major risk drivers in agricultural loan portfolio and designed to be consistent with Basel II, including consideration given to forecasting accuracy and model applicability. The significant risk factors are facility type, cropping pattern, borrower characters, cost of living, regional locations and collateral/security type beside borrowers' financial capacity and leverage position. The study also shows how agricultural exposures can be typically 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.

Introduction

A rapid growth in the rural economy and within that of agriculture in India is highly feasible provided key ingredients such as adequate supply of credit and the availability of the tools for the management of risks that agriculture is exposed to are religiously followed.

Farm level surveys have indicated that the most frequently cited risks are price, crop/weather and health. These risks among others could lower farmers' anticipated income and have negative effects on their standard of living, ability to provide for themselves and their families, ability to build capital and hence, their inherent creditworthiness. In order to sustain credit disbursement to agricultural farmers, public sector banks in India should be able to ease risk arising from credit exposure in agriculture. A good credit risk assessment assists banks and financial institutions in taking right and informed credit decisions, proper loan pricing, determining the amount of loans to be disbursed, reducing the chance of default and finally, increasing the possibility of debt recovery. Credit risk assessment involves determining the financial strength of the borrowers, estimating the probability of default and reducing the risk of non-payment to an acceptable level. In general, credit evaluations in public sector banks in India are based on the credit officer's subjective assessment of judgmental assessment techniques.

However, this technique seems to be inefficient, inconsistent and above all non-uniform because of subjectivity in choice of risk weights and scores, and hence,

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suboptimal. Rather, customized credit scoring model based on internal data of a bank has the potential of reducing the variability of credit decisions and imparting efficiencies to credit risk assessment process.

The New Basel Accord, scheduled to be implemented by the end of 2009, 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 according to primary commodity and geographical location. Agricultural lenders could then adopt similar models to quantify credit risk, a key component in the calibration of minimum capital requirements. Ramaswami *et al.* (2004) discussed the issue of risk management in agriculture in a comprehensive manner. Some of the risk-reducing strategies at the farmers' level have been crop diversification, intercropping, farm fragmentation and non-farm income.

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 borrowers' creditworthiness. Such a model would enable the bank to identify the 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 corporate exposures and retail exposures. Basel II allows agricultural loans to be categorized and treated as the retail exposures. However, portfolio credit risk models for agricultural loans are 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 is designed to be consistent with Basel II including the 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.

While 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 to farm typology, commodity, and geographical location. Credit risk of 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.

The objective of this study 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 in forecasting accuracy and applicability. We also highlight how such a model would help the Indian banks to mitigate risk in agricultural lending.

For individual farmers and agri-businesses, 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 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 its risk weights are also based on expert opinion. The weights should be grounded based on the historical experiences. Accordingly, we have followed a statistical model approach which takes care of the "5 Cs" subjectively and produces consistent forecast about the borrowers' default probability. Bank can use such a credit rating tool in 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., have been discussed later in detail) for portfolio credit risk model.

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

Research Methodology

While 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 contributed to the aggregate debt-servicing capacity and creditworthiness during the downward swings in farm income and reductions in asset value during the 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 serve as good leading indicator for the eventual creditworthiness 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 take into account commodity and regional differences. Economic performance in the agricultural sector is also widely influenced by events in both 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 the 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 a 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 and authenticity of data are more problematic in agricultural sector. However, in this pilot study, we have made an attempt to study the crucial factors that assumed to play an important role in credit risk of agricultural loan of a large public sector bank.

The credit risk is defined by 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 according to models and 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 (NPA) of the bank as defaulted loans. According to the Reserve Bank of India (RBI) definition of NPA, if the interest and/or installment of principals remain 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 the 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 that loan segment and to manage the risk systematically in these zones.

Score Card Building for Agricultural Loans (Critical Steps)

The following are the critical steps that have been undertaken to develop the Agri-Credit Score model:

- 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 and representative portion of recent accounts with known payment behavior, plus declined and or bad applications for each sub-population. In this case, we have received data of 900 borrowers from the bank over the period 1992-2007. However, due to lot of missing information, we had to reduce the sample to 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.

The Agri-Score Card Development Process

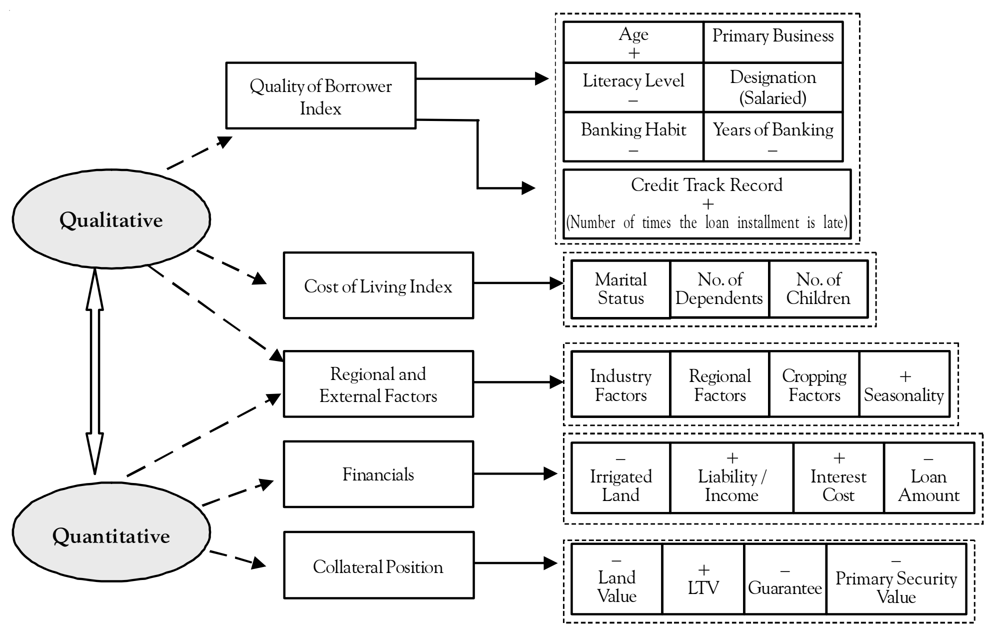
- Feasibility study
- Sample definition
- Data assembly
- Analysis of characteristics
- Reject inference
- Scorecard build
- Risk Differentiation
- Validation (on the basis of bank's internal data)
- Strategy selection and documentation
- Implementation

Data

Based on a sample data of 800 accounts from four circles, we tried to find out the major characteristics that would decide the nature of risk in agricultural loan. After finding out these parameters, we tried 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.

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 borrowers' 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 hypothetical relationship among these factors with the default probability. For example, "LTV" which is the ratio of the amount of loan outstanding over value of the security is positively related to default risk. It means, the higher is the ratio, the lesser is the proportion of collateral attached to the loan, and higher is the probability that the loan would default. Similarly, the higher is the value of the land, the lower is the chance of risk as indicated by the negative sign. Figure 1 documents the important risk parameters that a credit officer must look at objectively before sanctioning an agriculture loan proposal and weigh these factors to rate the agri-borrower.

Figure 1: Risk Parameters of Agriculture Rating Model



Empirical Analyses and Results

Table 1 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 coded=0 for standard assets. This is called 'binary dependent variable' where we are predicting the odd ratio Pr($DDEF/1–DDEF$). The 36 independent variables used in the logistic regression analysis are listed in the first column of Table 1 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 Table 1 along with their signs. The standard error of coefficients and hence the z-values (ratio of coefficients divided by standard errors) are reported in columns 4 and 5 of Table 1. 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 to as significant at 5% confidence level.

Table 1: Dependent Variable: DDEF
(this is a dummy and the value = 1 if loan is bad and value=0 if loan is good)

Independent Variables	Short Names	Coeffi-cients	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	0.00	0.00	0.00	0.00
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	0.00	0.00	0.00	0.00

(Contd...)

Table 1: Dependent Variable: DDEF (...contd) (this is a dummy and the value=1 if loan is bad and value=0 if loan is good)					
Independent Variables	**Short Names**	**Coeffi-cients**	**Std. Error**	***z*-values**	***P*>|*z*|**
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	0.00	0.00	0.00	0.00
Loan Type7 (Crop Loan)	loantypdum7	0.00	0.00	0.00	0.00
Loan Type8 (Crop Loan/Development Loan)	loantypdum8	0.00	0.00	0.00	0.00
Loan Type9 (Farm House)	loantypdum9	0.00	0.00	0.00	0.00
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 Type13 (Govt. Loan)	loantypdum13	0.00	0.00	0.00	0.00
Circle1 (Bangalore)	circld1	0.00	0.00	0.00	0.00
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

Note:
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 the number of estimated observations are 152;
3. & three types of prime securities are taken, =1 if Hypothecation, =2 for Hypothecation and Fixed Assets, =3 for Fixed Assets;
4. $ indicates the number of years the borrower is dealing with the bank.

It is important to note that factors reported in Table 1 have correlation among them and therefore have a 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, and 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. We have also examined the risk profile of different age groups (group 1 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 the first age group (i.e., 22-42) are much safer than those in 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 Equation

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

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 for a particular loan proposal. If a particular parameter is missing, the logit Z score value would not give the correct picture about the creditworthiness of the borrower. Therefore, to ensure accurate 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). Therefore, by using the above logit Z score equation, a loan officer will obtain a score for the borrower to predict its rating.

It is important to note here that we have used lot of dummies (such as loan type, 13 dummies: loantypdum1–loantypdum13; 4 crop dummies: cropdum1–cropdum4; 4 circle dummies: circld1–circld4) to control for difference in loan characters, crop types and regions. Suppose a borrower has taken a KCC loan, then loantypdum1 will be =1. To capture its effect, 1 will be multiplied by the respective weight coefficient (here it would be –5.6681) and other dummies would be =0. Similarly, if the KCC loan is for traditional crop, i.e., crop type 1, cropdum1 should be taken as 1 and other crop dummies will be zero and this 1 should be multiplied by 3.8408 to see its impact on the logit Z score.

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:

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

where '*exp*' is the exponential function whose value is approximately 2.718281828.

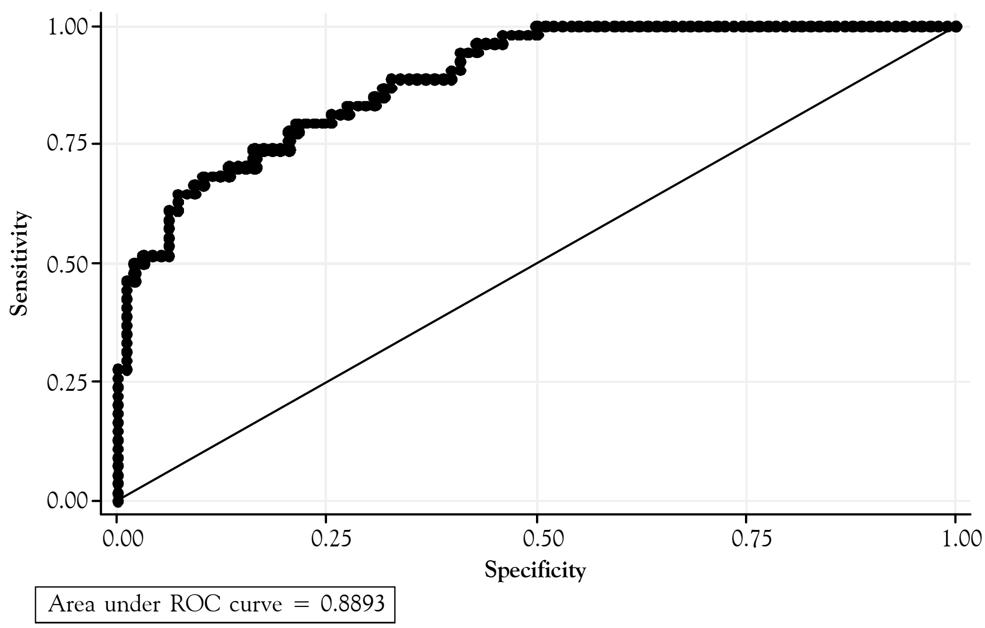
After EPD is obtained, the loan facility can be classified into the following risk buckets through internal mapping (Table 2). The internal mapping exercise is being done by comparing the model's predicted EPD (based on the logit score obtained) with the actual default rates being various percentiles. This calibration exercise for risk bucketing is done for the sample 800 accounts over the period 1992-2007 from the data obtained from the bank.

Table 2: Model Calibration Through Internal Risk Mapping		
PD Ranges (Fraction) (in %)	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

Validation

We have performed within sample validity of our agri-credit scoring model. Figure 2 shows the proportion of defaulted loans vis-à-vis the proportion of solvent loans predicted by the logit Z score model. The 45° diagonal line is a reference line which shows randomness in the prediction. Since the concave line is above the 45° 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 graph: Figure 2) is able to capture greater proportion of defaulted loans and

Figure 2: Receiver Operating Characteristic Curve Measuring the Discriminatory Power of the Model



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.

Deriving the Final Risk Weights

Finally, we derive the risk weights by using the coefficients of the regression equation presented in Table 1 (and also in the Z-score equation). The weights reported in Table 3 depict the actual contribution of these factors on the creditworthiness of the borrowers.

One can observe from Table 3 that 'regional and external factors', and 'collateral position' contribute more in assessing the creditworthiness of the agricultural loan seekers. As far as other factors are concerned, the bank needs to look at the relevant documents submitted by the borrower, the presence of government subsidy, market condition of the

Table 3: Factors and Their Contributions to Default Risk in Agriculture Loan

Risk Parameters	Weights (in %)	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 and 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**	

agricultural products (price movement, production, etc.) as additional factors to closely monitor the risk profile of the agri-portfolio.

Advantages of Agri-Credit Scoring Model

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

- Objectivity and 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; and
- It strengthens banker-borrower relationship because of transparency in loan decision making process.

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 links with characteristics.
- Therefore, better risk management implies more loans with same effort, greater outreach, more market share, and greater profits; and
- The greatest benefit: strengthens the credit culture of explicit and conscious risk management.

Agriculture Risk Profile in the Bank Under Study

Tables 4 and 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

Table: 4: Portfolio Risk Profile of the Bank in Agriculture Loan Segment: Farm Loan Risk

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**	

of loans are concerned, Table 5 documents the fact that Kishan Credit Card (KCC) loans have the highest risk of defaults (38.62%) followed by Land Development loans (18.28%) and Farm Machinery loans (10%).

Table: 5: Portfolio Risk Profile of the Bank in Agriculture Loan Segment: Default Risk

Year: 1992-2007

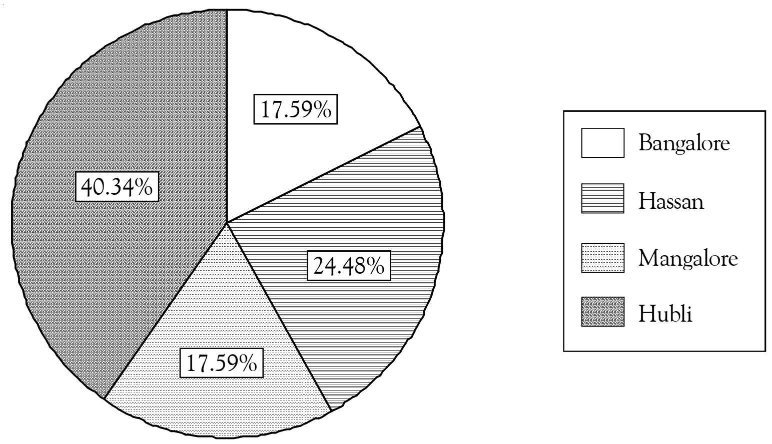
Sl. No.	Loan Type	Total *N*	Solvent *N*	Defaulted *N*	Relative Default %	Default % to Total
1.	KCC	328	216	112	38.62	14.00
2.	KCC and Development	20	20	0	0.00	0.00
3.	Land Development	115	62	53	18.28	6.63
4.	Farm Development	47	37	10	3.45	1.25
5.	Tractor Loan	48	35	13	4.48	1.63
6.	Vehicle Loan	36	27	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.	Government 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 may be carried out to find out the risk characteristics of each loan. However, logit Z score equation and the regression results reported in Table 1 take care of this problem. As already being discussed, each loan character is captured by the respective dummies that have been reported in Table 1. Hence, if anybody is interested to see the risk in a particular facility or crop or region, he has to refer to the specific code being given for each type (or call dummies) and will get the predicted score and risk factors accordingly. Therefore, 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.

Circle-Wise Default

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.

Figure 3: Pie Chart Depicting Risk Profile of Circles

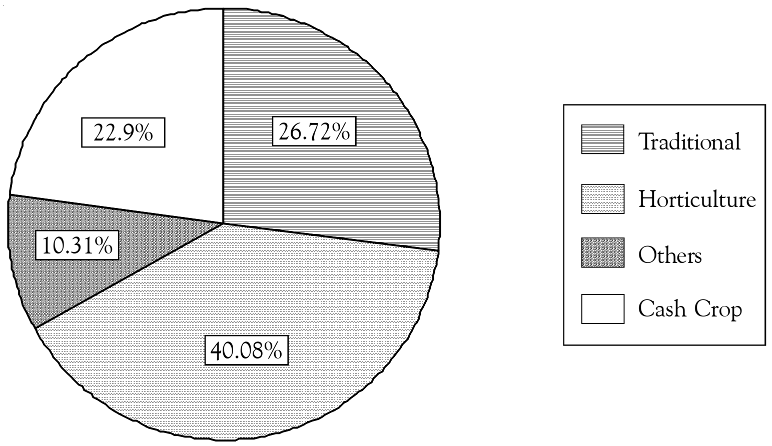


(Total number of defaulted loans = 290)

Crop-Wise Default

Figure 4 portrays the crop-wise portfolio risk composition. One can notice that most of the defaulted loans are from horticulture (40.08%) followed by traditional crops (26.72%) and cash crop items (22.9%). Others mean not classified (meager 10.31%) due to the non-availability of information.

Figure 4: Pie Chart Depicting Risk Profile of Crops



Portfolio Management Strategy

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

Probability of Loan Loss:

Expected Loan Loss: $EL=PD\times E\times LGD$

PD: Probability of Default, E=Credit Exposure and LGD: Loss Given Default=1 – Recovery Rate.

Unexpected Loan Loss: $UL=E\times LGD\times PD\times(1-PD)$

Entire Portfolio Loss: *Expected Loss* – EL_p= *sum of individual EL*

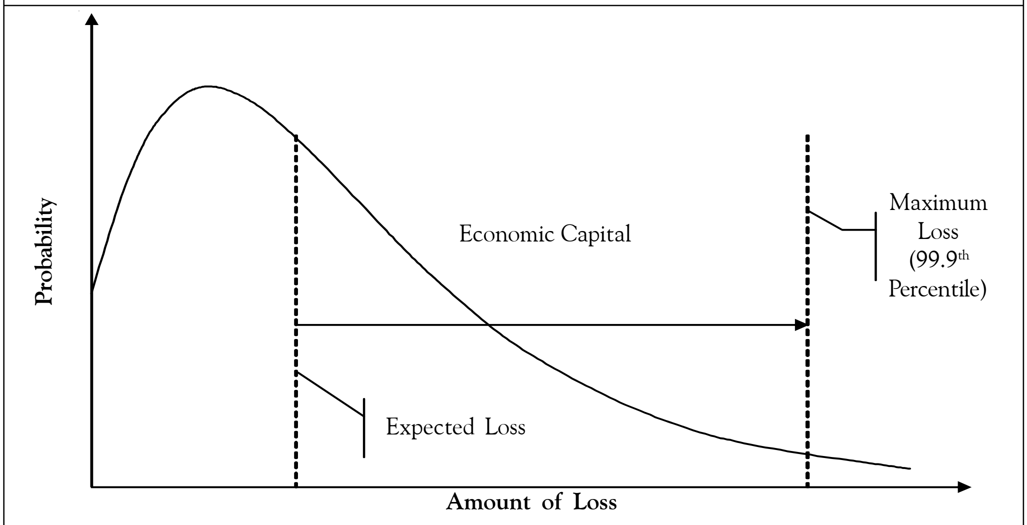
Unexpected Loss – UL_p= *Sum of the risk contributions of individual loans.*

Risk contributions either can be set by the bank in terms of risk exposures or need to be estimated by finding out the loss contribution of each segment (by region/rating/industry) to total segment.[1]

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 (Figure 5) 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, a bank has to first estimate the pooled Probability of Default (PD) on retail-agriculture loan. This pooled PD can either be obtained by counting rating-wise default numbers by generating a pool and count the default numbers in the same way we have done in Tables 4 and 5.

[1] For more details, see "The Fine Line Between Managing Concentrations in Credit Risk and Managing the Credit Risk Concentrations", *Risk Analysis Service, RMA*, February 2006, Vol. 2. Also see Bandyopadhyay (2007).

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). 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 a borrower has taken many facilities, obtain average LGD rating (we may reallocate the collateral in such cases where multiple facilities are taken). After multiplying PD with anticipated LGD, we will get expected loss % (EL%). Now in terms of EL%, rank the borrowers from the lowest EL to the highest EL. Suppose, you have 10 rankings, the lowest will receive the best grade (grade 1) and the worst (with the 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.[2]

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 provides a risk-adjusted common currency of risk so that banks can compare the risk adjusted profitability of their 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 banks can use economic-capital-based analysis to explore the profitability of their portfolios in terms of credit score.

Conclusion

This study presents a credit scoring model for agricultural loan that we have developed based on the sample data obtained from a large public sector bank in India. After giving an overview of the key issues in credit risk management of agricultural loans, the study discusses the major risk drivers and their importance in assessing the creditworthiness of

[2] See M Featherstone *et al.* (2006) for rating mapping process.

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 logistic scoring model development process elaborated in this study reflects major risk characteristics of agricultural loan segment will increase transparency in lending decisions, understanding of risks and assist the bank in managing the risk. The results of the model would complement the bank in making portfolio management decisions and increases the transparency in their decision-making process. This study also shows how the agricultural exposures can be managed on a portfolio basis. This will enable the bank to diversify the risk and optimize the profit in the business which will ultimately enable them to comply with the Basel II requirements under the advanced approach. This will strengthen the banker-borrower relationship and enables the bank to expand its reach to farmers because of transparency in loan decision-making process.

However, it is important to note that the 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 its utility to explore and expand the scope for further research. ❖

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