CREDIT RISK ASSESSMENT AND THE OPPORTUNITY COSTS OF LOAN MISCLASSIFICATION

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Credit portfolio management involves the identification and monitoring of loans across various risk classes. The performance of loan accounts determines the stability and profitability of financial institutions and it is for this reason that financial institutions screen loan applications before making credit decisions, and review existing loan accounts to decide the level of monitoring required. Despite the on-going development of statistical credit scoring models most models used by lenders or recommended by academics fail to explicitly consider lenders' profit maximizing objective, although profit maximization is usually assumed implicitly. The purpose of this paper is to present an alternative view of the credit assessment problem which explicitly includes the opportunity costs of misclassifying an acceptable or unacceptable loan. We review first traditional approach of credit assessment and then extend these models (i.e. Logit) to include the costs of misclassification. Assuming a profit maximizing objective we then establish the new selection criteria. This criteria is compared against a Logit model using Canadian Farm Credit Corporation loans data.

Credit Assessment and the Costs of Loan Misclassification

To combat asymmetric information many lenders in Canada and the United States have adopted formal credit evaluation models to screen loan applicants (Ellinger et al). Most credit assessment models can adequately predict the loan worthiness of a large portion of loans, but, none are perfect and are subject to error. In loan classification models there are two types of errors: Type I error refers to accepting a loan which is actually of high credit risk, and Type II error refers to rejecting a loan which is of low credit risk.

In both these cases the lender loses profits. For Type I error losses include not only lost principal, but also lost interest on principal during the period of litigation and foreclosure. In addition to loan losses there are incremental increases in administrative costs, legal fees, insurance costs, and property taxes. For Type II error, the lender foregoes the revenues associated with a good loan. Although it may be argued that rejecting a good loan is not too costly, it can be if the alternative loan is of high credit risk, so that full recovery of lost revenue may not be obtainable. The costs of Type I error are more visible since they are observed through loan losses, and loans which are temporarily in arrears. Type II error is not often observable because the ultimate disposition of the rejected loan is unknown.

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It is customary to define the expected profit from a loan advanced given the possible alternatives in repayment (i.e possibilities of regular repayment, temporary default and, foreclosure), considering only the cost of Type I error. The important thing to note is that the opportunity cost of lost interest income by rejecting a good loan (cost of Type II error) is not explicitly considered in the lenders profit functions. In order to increase the expected profit, the lending decision must include the opportunity cost of lost interest income by rejecting a good loan and in this context the inclusion of costs associated with Type II error in a credit scoring model is as important as including the cost of Type I error.

In formal (Logit, Probit credit scoring models etc.) and informal (ad hoc) credit scoring models the group assignment rule is based purely on the predicted probability of default (or other scoring criteria) in which a loan is accepted if it scores below a given cutoff and rejected otherwise. Such criteria implicitly assume that the costs of Type I and Type II errors are equal. In practice, these costs cannot be equal. If the costs of misclassification are not equal alternative criteria must be considered in which predicted default probabilities or likelihood values must be weighted by their respective costs of misclassification. In doing so there becomes an explicit trade off between the probability of default and cost of Type I error on the one hand and between the probability of repayment and cost of Type II error on the other hand. For example, if the predicted probability of default of a borrower is lower than the probability of repayment and the associated cost of Type I error is much larger than the cost of Type II error, then the lender will be better off by classifying that borrower as bad than as good. This study incorporates these opportunity costs into the credit assessment criteria to minimize the costs / maximize the profits to the lender.

Cost of Type I Error

The cost of Type I error is the cost of losing some portion of principal and interest on principal during the process/period of loan foreclosure. The incremental increase in administrative costs, legal costs, costs of taking possession, maintaining, and disposing the secured assets, and the concessions given by lowering the interest rate and/or waiving some portion of accumulated interest and/or principal increases the Type I error loss to the lender. Thus the cost of misclassifying an unacceptable loan (type=1) as an acceptable loan (type=0) can be defined as

$$(1)\quad C(0/1)=([a(1+r)+b(1+r)^2+c(1+r)^3+d(1+r)^4+COST\text{-}AR]-[s*SL])*(PLL/\pi_1) +TCOST*(1-[PLL/\pi_1]).$$

Where,

- r is the interest rate
- a is the proportion of loans in default for less than 1 year
- b is the proportion of loans in default for more than 1 year but less than 2 year
- c is the proportion of loans in default for more than 2 year but less than 3 year

- d is the proportion of loans in default for more than 3 year
- $a(1+r)+b(1+r)^2+c(1+r)^3+d(1+r)^4$ is expected gross uncollected interest i.e the amount of income that could have been earned had the repayment been regular
- COST includes the costs of taking possession, maintaining (insurance premium, property tax etc.), disposing of the secured assets, legal costs, increased administrative costs and concessions given (waiver of a portion of accumulated interest and/or principal and reduction of the interest rate charged) in case of foreclosed loans
- TCOST is the costs of recovering the loan amount in temporary default which includes legal costs/lawyer notice fee, increased administrative costs and concessions given (waiver of a portion of accumulated interest and/or principal and reduction of the interest rate charged) in case of loans which are in default temporarily
- AR is the amount of income, including the rental income from the secured property, if any received during the process
- s is the security value trend adjustment factor
- SL is the security-to-loan ratio.
- PLL is the probability of loan loss

The expected cost of Type I error is the magnitude of loss for a $ loan when an unacceptable borrower is accepted as an acceptable borrower by the model. It can be seen that this cost consists of two components; one, the cost associated with loans that will be foreclosed and two, the cost associated with loans that will be in default temporarily. The assumption here, which is realistic also, is that foreclosed loans will be from the default group (i.e first a loan will become default and when there is no chance of recovery of arrears by usual follow-up/persuasion, lenders will go for foreclosure). So there is PLL/π_1 probability of a defaulted loan being foreclosed and $1-(PLL/\pi_1)$ probability of being in default temporarily.

Cost of Type II Error

The cost of Type II error is the opportunity cost of foregone revenue associated with a good loan. Though the cost of Type II error is not observable, and it can be argued that rejecting a good loan is not too costly, it can be costly if the alternative loan is of high credit risk. In this case, the lost revenue may not be obtainable and the cost of Type I error in the alternative loan adds to the cost. So Type II error is also equally important as far as the lender's profit is concerned. Thus the cost of misclassifying an acceptable loan (type=0) as an unacceptable loan (type=1) can be defined as

$$(2) \qquad C(1/0)=r-(\pi_0*r)+\pi_1\{([a(1+r)+b(1+r)^2+c(1+r)^3+d(1+r)^4+COST-AR]- [s*SLB])*(PLL/\pi_1)+TCOST*(1-[PLL/\pi_1]).$$

Where r, a, b, c, d, COST, TCOST, AR, s, PLL are defined as above and SLB is the average security to loan ratio.

The expected cost of Type II error is the magnitude of loss for a $ loan when an acceptable borrower is rejected as an unacceptable borrower by the model. This consists of three components. The first component is foregone interest income (r) by rejecting a good loan. The second and third components are based on the assumption that the lender will not keep the un-lent money idle and will lend that money to an alternative borrower. This alternative borrower, once again, may be good or bad. There is π_0 probability of this borrower being good and π_1 probability of being bad. So lender can get r interest income with π_0 probability and loose

$$[a(1+r)+b(1+r)^2+c(1+r)^3+d(1+r)^4+COST-AR]-[s*SLB])*(PLL/\pi_1)+TCOST *(1-[PLL/\pi_1]$$

with π_1 probability in the alternative loan.

These costs of misclassification cannot be negative. That is there may not be any cost to the lender, but there cannot be any gain by misclassification. So these costs can be either greater than, or equal to, zero.

Properties of Costs of Type I and Type II Errors Compared

In this section, the costs of Type I and Type II errors are compared and discussed with respect to variables of influence.

(i) The relation between the change in costs of Type I and Type II errors for a unit change in interest rate (r) depends on the probability of default (π_1) and the probability of loan loss (PLL). This relation can be summarised as follows:

(3) $\partial C(0/1)/\partial r = \partial C(1/0)/\partial r$ if $\pi_1 = \sqrt{PLL}$

(4) $\partial C(0/1)/\partial r > \partial C(1/0)/\partial r$ if $\pi_1 > \sqrt{PLL}$

(5) $\partial C(0/1)/\partial r < \partial C(1/0)/\partial r$ if $\pi_1 < \sqrt{PLL}$

The change in costs of Type I and Type II errors for a unit increase in interest rate (r) will be equal when $\pi_1 = \sqrt{PLL}$. If $\pi_1 > \sqrt{PLL}$, then a change in the cost of Type I error will be more than a change in the cost of Type II error. If $\pi_1 < \sqrt{PLL}$, then a change in the cost of Type II error will be more than a change in the cost of Type I error.

(ii) For a unit increase in COST and TCOST, the increase in the cost of Type I error is $1/\pi_1$ times more than the increase in the cost of Type II error.

(iii) Similarly, for a unit increase in AR and SL, the change in the cost of Type I error decreases $1/\pi_1$ times more than the change in the cost of Type II error.

(iv) For a unit increase in probability of loan loss, the cost of Type I error changes $1/\pi_1$ times more than the cost of Type II error changes; the direction of change depends on the values of LOSS[1] and TCOST.

(v) A unit increase in π_1 increases the cost of Type II error by interest rate (r), whereas the direction and size of change in the cost of Type I error depends on the values of TCOST and LOSS.

(vi) There is no relationship between probability of loan loss and probability of loan default as far as the cost of misclassifying a current loan as a non-current loan is concerned. There is a relationship between these two as far as the cost of misclassifying a non-current loan as current is concerned. But, the size and direction depends, once again, on the values of LOSS and TCOST.

Theory and Methodological Design

To examine loan acceptance criteria based on the opportunity costs of loan misclassification rather than probability cut-offs relative probability that a farm

[1]LOSS = $a(1+r)+b(1+r)^2+c(1+r)^3+d(1+r)^4$+COST-AR-[s*SL] i.e the amount of loss for a $ loan in case of foreclosure.

with observed characteristics x_i (such as debt to asset ratio, liquidity ratio etc.) is drawn from the delinquent or non-delinquent group can be estimated. In this case the existence of well-defined groups is presumed, so that the focus is only on the problem of deciding how to classify, as yet, unknown observations to obtain least expected loss to the lender.

Prediction

Classification probabilities and rules are constructed in an intuitively appealing fashion by comparing the two group likelihood functions. If the two groups are not of the same size, the likelihood must be weighted before they can be compared. Let π_0 be the a priori probability of an observation being drawn from group 0 (good loans), and π_1 be the priori probability of an observation being drawn from group 1 (bad loans). Let us choose regions R_0 and R_1 such that if the sample point falls in R_0, we classify the individual into group 0, and if it falls in R_1 we classify the individual into group 1. Suppose, the researcher perceives the cost of misclassification of C(0/1) and C(1/0), where C(i/j) is the cost of classifying an observation as group i when it truly belongs to group j. Following Anderson (1958) and Maddala (1983), the expected total cost of misclassification is

(6) $$Miscost = C(1/0)\pi_0\int_{R_1} f_0(x_n)\,dx + C(0/1)\pi_1\int_{R_0} f_1(x_n)\,dx.$$

Because

(7) $$\int_{R_1} f_0(x_n)\,dx + \int_{R_0} f_0(x_n)\,dx = 1$$

We have
(8)

$$Miscost = C(1/0)\pi_0[1-\int_{R_0} f_0(x_n)\,dx] + C(0/1)\pi_1\int_{R_0} f_1(x_n)\,dx$$

$$= C(1/0)\pi_0 + \int_{R_0}[C(0/1)\pi_1 f_1(x_n) - C(1/0)\pi_0 f_0(x_n)]\,dx$$

This *Miscost* is minimized if R_0 is chosen so that

(9) $$C(0/1)\ \pi_1\ f_1(x_n) < C(1/0)\ \pi_0\ f_0(x_n).$$

Thus the classification rule for minimizing the expected costs of misclassification would be to assign an observation with characteristics index x_i to group 0 if

(10) $$\frac{f_0(x_n)}{f_1(x_n)} \geq \frac{C(0/1) \times \pi_1}{C(1/0) \times \pi_0},$$

and to group 1 otherwise.

It can be noticed that if costs of misclassification are equal i.e C(0/1)=C(1/0), then the classification rule is identical to assigning observations to the group with the highest probability. But in practice, these costs of misclassification are not equal.

Predictive Accuracy

The prediction accuracy involves a comparison of the predicted acceptable and unacceptable observations with the actual current and non-current observations. In Logit model the prior probabilities will be used as a cutoff to classify the borrowers as acceptable or not. Using the prior probability as a cutoff point is the latest advocation in the agricultural credit scoring techniques (Miller and LaDue,1989). This is done by determining the percentage of current and non-current loans in the sample. These percentages are used as the prior probabilities and on the basis of this a borrower will be classified into one of the categories. The prediction accuracy is assessed in the same way as in Cost minimization model.

Lender's Profit/dollar Loan

The performance of any credit scoring model should not be judged purely on the basis of its prediction accuracy or the proportion of errors. The opportunity costs associated with Type I and Type II errors in prediction are also important. To assess the performance of the Cost minimization model relative to the performance of the Logit model, we should have a common measure which can consider both the prediction accuracy and the opportunity costs of errors in prediction. Because the prediction accuracy of the Logit model may be more than the Cost minimization model, the opportunity costs associated with Type I and II errors may be less in the Cost minimization model. In this case it is not possible to compare the models' performances. The differences in the proportions of errors (Type I & II) and in the opportunity costs of these errors in prediction can be captured in the lender's profit / $ loan.

The model's expected lender's profit function for $1 loaned would be

$$(11) \qquad \frac{N_{00}}{N} \times \bar{r} + \frac{N_{10}}{N} \times -C(0/1) + \frac{N_{01}}{N} \times -C(1/0) + \frac{N_{11}}{N} \times$$

where

N = total number of borrowers

N_{00} = the number of borrowers classified as acceptable who are current

N_{01} = the number of borrowers classified as unacceptable who are current

N_{10} = the number of borrowers classified as acceptable who are non-current

N_{11} = the number of borrowers classified as unacceptable who are non-current
$\bar{r}$ = average interest income/dollar loaned

C(0/1) = cost of loaning a dollar by classifying a non-current loan as acceptable

C(1/0) = opportunity cost of not loaning a dollar by classifying a current loan as unacceptable

It may be noted that this profit of the lender is not the actual profit earned by lending. This profit function is credit scoring model's lender's profit function. From this we can only calculate the difference in the magnitude of expected profit between the Cost minimization and the Logit models given lending decisions are taken using these models.

Data and Model Variables

The data for this study were provided by the Farm Credit Corporation of Canada. The loans advanced during 1981 to 1988 and remaining outstanding as of January 31, 1992 were used. Data consist of 26 variables on 12668 loans.

Based on the relevance of the variables to loan default and their usage in past research (Lufburrow et al.; Barry and Ellinger; Miller and LaDue; Turvey and Brown; Turvey) the ratios of liquidity, profitability, leverage, efficiency, repayment ability and, security were used as the explanatory variables . The FCC also uses these variables in its Business Management Framework tools. Since the FCC loans are distributed across different regions and farm types, region and farm type dummy variables were used to capture the variations across region and farm type. These model variables are generated using existing variable definition. In addition to this, relevant data/information for computing the opportunity costs of misclassification are also collected i.e costs include maintaining the collateral during the loan foreclosure process (maintenance cost, insurance premium, property tax etc), the average length of time the loans will be in default once the foreclosure process is started, changes in collateral market value, legal costs, the amount of income received during the process, and the amount of interest and /or principal waived and interest rate lowered in case of negotiated settlements.

Validation of the Results of the Models

Using the same sample for estimation of the model and evaluation of the prediction accuracy may result in overly optimistic prediction accuracy. To overcome this problem the sample is first divided randomly into two sets - 75% of the data for estimation of the models and 25% as a hold-out sample for validating models results. The sample set was divided into two sets by random number choice. So the cases in the hold out sample are independent of the cases used in the estimation of the model and both the sets are drawn from the same distribution.

Results and Discussion

In this section we discuss the results of the analysis of the Cost minimization model and compare it with the results of the Logit model. The results of both these models are validated using hold out sample. We give empirical evidence to show the superiority of the Cost minimization model over the well recognised Logit model.

Estimation of the cost components

The information on interest rate (r), security to loan ratio (SL), probability of loan loss (PLL), and prior probabilities of current and non-current loans (π_0 and π_1) were readily available in the data provided by the FCC. Information on COST, AR, and TCOST are not readily available but estimates of these costs were collected by discussing the details with the officers of the FCC.

Classification Assignment Rules With The Opportunity Costs of Loan Misclassification

The group assignment rule in existing credit scoring models is purely based on the predicted probability of default with the costs of misclassification assumed to be equal. These costs, as defined earlier, are not equal. The inclusion of these costs results in a different assignment rule, than in the traditional models. It can be seen from the assignment rule in equation 10 that the likelihood functions (likelihood of being accepted and unaccepted) are weighted by their respective costs of loan misclassification. The difference in the costs of loan misclassification changes the weighted likelihood functions and their ratios. This results in change in assignment of observations to acceptable and unacceptable groups.

Of the 8718 observations of test sample, both the models predicted 4238 observations as acceptable and 1854 as unacceptable i.e 69.88% of observations are common in prediction (Table 1). The models differ in predicting the remaining 30.12% observations. 2611 observations predicted as unacceptable by the Logit model are predicted as acceptable by the Cost minimization model and 15 observations predicted as acceptable by the Logit model are predicted as unacceptable by the Cost minimization model. These results indicate how inclusion of costs of misclassification results in difference in predictions.

Table 1. Comparison of Group Assignment of Observations in Cost Minimization and Logit Models

Particulars of Prediction	Actual		
	Current	Non-current	Total
Predicted as acceptable by both the models	3488	750	4238
Predicted as unacceptable by both the models	833	1021	1854
Predicted as acceptable by Cost minimization model and unacceptable by Logit model	1426	1185	2611
Predicted as unacceptable by Cost minimization model and acceptable by Logit model	11	4	15
Total	5758	2960	8718

Evaluation of Predictive Accuracy of The Cost Minimization Model Relative to The Logit Model

The lender's profit not only depends on the prediction accuracy, but also on the opportunity costs of loan misclassification. Thus profits are maximized when the prediction accuracy is maximum and the costs of misclassification are minimum. The empirical results of the Cost minimization model indicates that the model meets this requirement. The extent of the superiority of this model is evaluated by comparison with the Logit model. The results of the prediction accuracy, the costs of Type I and II errors and, the expected lender's profit of the two models are compared in this section.

Comparison of Prediction Accuracies

The prediction accuracies of the Cost minimization and Logit models are

Table 2. Comparison of Prediction Accuracies of The Cost Minimization and The Logit Models

Particulars of Prediction	Cost Minimization Model		Logit Model	
	Test Sample	Hold-out Sample	Test Sample	Hold-out Sample
Prediction Accuracy (%)	68.12	66.93	65.44	60.23
Proportion of Current Loans Correctly Predicted (%)	85.34	84.81	60.77	49.06
Proportion of Non-current Loans Correctly Predicted (%)	34.63	32.12	74.53	81.97
Proportion of Type I Error (%)	65.37	67.88	24.47	18.03
Proportion of Type II Error (%)	14.66	15.19	39.23	50.94

presented in table 2. An overall prediction accuracy of the Cost minimization model of 68.12% is higher than the 65.44% obtained from the Logit model. Type I error (65.37%) is higher and Type II error (14.66%) is lower with the Cost minimization model in contrast to a Type II error (39.23%) and of Type I error (24.47%) obtained from the Logit model.

It can also be seen that the overall prediction accuracy of the Cost minimization model in the hold-out sample is 66.93% as against 60.23% of the Logit model. It can be observed that the prediction accuracy of the Cost minimization model in the hold-out sample has dropped by only 1.19% compared to the test sample, whereas this drop is 5.21% in the Logit model. This implies that the Cost minimization model is more consistent in prediction. As in the test sample, in the hold-out sample, there was more of Type I error (67.88%) and less Type II error (15.19%) with the Cost minimization model and more of Type II error (50.94%) and less of Type I error (18.03%) with the Logit model.

Comparison of Average Costs of Type I and Type II Errors and Expected Lender's Profit

Not only the proportion of errors but also the opportunity cost associated with each \$ of loan in error is important. The opportunity costs for both Type I and Type II error for a \$ loan is lower for the Cost minimization model compared to the Logit model (Table 3). The cost of Type I error per \$ loan is 0.1166 in the Cost minimization model and it is 0.1172 in the Logit model. Similarly, the cost of Type II error is 0.0692 in the Cost minimization model and it is 0.0757 in the Logit model.

The differences in the proportions of errors (Type I and II) and the economic consequences associated with the average costs of these errors are captured and compared in the expected lender's profit. The expected lender's profit takes both the proportions and average costs of these errors (equation 11) into consideration; it is used as a yard stick to compare these models. The expected lender's profit is 0.0328 in Cost minimization model as against 0.0158 of Logit model. It indicates that the expected lender's profit is 1.7% more in the Cost minimization model than in the Logit model. In the hold-out sample also, the opportunity costs for both Type I and II error for a \$ loan is less and the expected lender's profit is more in the cost minimization model compared to the Logit model.

Thus, the performance of the Cost minimization model outweighs the performance of the Logit model. The Cost minimization model performs better than the Logit model both in prediction accuracy and also in minimising the costs associated with the errors it makes.

Table 4.9 Comparison of Costs of Misclassification and Expected Lender's Profit of Cost Minimization and Logit Models (per $ loan)

Particulars of prediction	Sample	Number of Loans		Average Interest Income ($)		Average Cost ($)		Expected Lender's Profit ($)	
		CMM*	LM**	CMM	LM	CMM	LM	CMM	LM
Current loans correctly predicted	Test	4914	3499	0.1159	0.1135	-	-		
	Holdout	1630	943	0.1160	0.1134				
Current loans predicted as unacceptable	Test	844	2259	-	-	0.0692	0.0757		
	Holdout	292	979			0.0687	0.0757		
Non-current loans predicted as acceptable	Test	1935	754	-	-	0.1166	0.1172		
	Holdout	670	178			0.1167	0.1188		
Non-current loans correctly predicted	Test	1025	2206	-	-	-	-		
	Holdout	317	809						
Total Loans	Test	8718	8718					0.0328	0.0158
	Holdout	2909	2909					0.0312	0.0040

* cost minimization model
** logit model

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