# Credit Scoring Models: A Comparison between Crop and Livestock Farms

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**Abstract**

This paper uses FBFM (Illinois Farm Business Farm Management Association) data to analyze several key factors in the decision to categorize borrowers into acceptable or problematic and to classify borrowers across five classes.  Net worth does not play significant role in the decision process for livestock farms, whereas it is significantly important for crop farms. For livestock farms, tenure ratio is not significant across classes and is generally not significant across categories depending on the cut off point used to describe acceptable or problematic borrower. However, it is significant for crop farms. Working capital to gross farm return, return on farm assets, and asset turnover ratio are all significant for both farm types. The operating expense to gross farm return is not an independent variable for livestock farms whereas an independent and significant variable for crop farms.



*Key words:* acceptable borrower, classes, credit scoring, crop farms, cut off point, livestock farms, and problematic borrower.

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## I) Introduction

Proposed in 1988, the Basel I Capital Accord, set guidelines for minimum capital requirements for financial institutions based on their exposed credit risk. Even though it was intended for G10 countries, it was adopted by 120 countries. One disadvantage of Basel I was that it did not differentiate financial institutions' credit risk by counterparty or loan. Banks with different risk exposures and risk ratings could have the same capital requirements. Basel II is an improvement over Basel I. It uses credit ratings from external rating agencies to define the categories and weights, and these categories and weights are individualized for the assessment of credit risks of each financial institution (Mendoza & Stephanou, 2005). Consequently, under Basel II, there is not a single risk measurement and capital management approach. They are adjusted for the characteristics of diverse financial institutions (Featherstone, Roessler, and Barry, 2006). Hence, under Basel II we see more refined models for determining capital requirements and these models change based on the different credit risk exposure and risk ratings of each financial institution.

Basel II's recognition of different loan types is consistent with the Farm Credit System's treatment of agricultural loan types. For instance, the Farm Credit System which is the major lender for agricultural loan, has 5 aggregate loan types - commercial farm loan, farm real estate loan, agribusiness loan, rural housing loan, and small loans. Each of these loan types uses its own credit scoring model. Thus, this implies that in its credit evaluations, the Farm Credit System recognizes the diversity in agriculture. However, this raises the question whether differences in types of farms within the commercial farm category should be considered. Among farm types, there are considerable differences in rates of return on assets, leverage ratios and liquidity. For instance, Boessen, Featherstone, Langemeier, and Burton (1990) identify large differences between the return on assets and leverage ratios for swine farms, and beef cow herd farms, with swine farms having three times more return on assets rates than beef cow herd farms and a leverage ratio of 0.25 compared to 0.16 for beef cow herd farms. Due to differences between farm types, the Farm Credit System might need to extend their risk rating system by applying different models for different farm types. These multiple credit scoring models can prevent costs of misclassifying borrowers that might be caused by not differentiating between farm types.

The misclassification problem exists also for regional credit scoring models. Lenders located in different regions typically have different credit scoring models. For instance, lenders in Illinois use a different credit scoring model than a lender in another region. However, each lender uses a single credit scoring model for all farm types and this credit scoring model is more representative of the farm type dominant in that region. For instance, Miller and LaDue (1989) developed a credit scoring model for a bank in New York and focused on dairy farms, while Luftburrow, Barry and Dixon (1984) for pricing purposes developed only one credit scoring model for five production credit associations in Illinois, with three of these associations focusing on grain farms and two other associations having more diverse borrower types including hog, dairy and beef farms. Even though separate models have been developed for separate regions, these models do not take into consideration the variability in farm types that exist in the same region. Separate models are needed for the same region across farm types to prevent misclassification of borrowers.

In the US, the development of different credit scoring models for a region has not been examined, but such research has been done for Canada. Turvey and Brown (1990) found that for Canada’s Farm Credit Corporation, farm type played an important role in the development of credit scoring models.

The Illinois Farm Business Farm Management Association has analyzed farms' financial measures by farm types: hog, grain, dairy and beef. This analysis shows that financial characteristics differ across hog, dairy, beef and grain farms in Illinois. Due to the differences in financial characteristics across farm types, it is expected that the system reflects differences in farm types in Illinois.

Based on the call by previous research for analyzing different farm types (Splett et al.,1994; Phillips and Katchova, 2004; Lufburrow, Barry, and Dixon, 1984) and the expectation that the system reflects differences in farm types in Illinois, the objective of this study is to: 1) to examine the important factors that determine the overall creditworthiness of a borrower by logit model, 2) to analyze whether credit scoring models differ across livestock farms (including hog, dairy, beef) and crop farms (grain farms) in Illinois.

The results will be informative to lenders as they consider further extensions and refinements of their risk rating systems in response to the new Basel Accord. Using models specific to farm types will reduce the costs of misclassification, and provide more equitable treatment of alternative farm types, risk-adjusted pricing across farm types, and greater efficiency in credit valuation. Further, the costs for implementing and extension of multiple credit scoring models to include farm types will be relatively low and subsequent operating costs will be minimal given that data are available and the estimation procedure is in place.

## II) Literature review

Nayak and Turvey (1997) argue that the misclassification arises due to asymmetric information and adverse selection. Lenders use screening devices to prevent adverse selection. One screening device lenders use is to offer high interest rates to all borrowers. The problem with this approach is that borrowers may not fully understand the underlying risks associated with these high interest rates. An alternative screening device is to use a credit scoring model which provides an objective measure of borrower risk. Even though credit scoring models do not eliminate the asymmetric information and adverse selection, they minimize it. Many lenders in US and Canada have adopted formal credit evaluation models to minimize adverse selection and asymmetric information.

Nayak and Turvey (1997) also state that misclassification errors can be categorized under two types, type 1 and type 2 errors. Type 1 error occurs when a bad borrower is accepted as a good borrower resulting in adverse selection of high-risk borrowers. The cost of this error are the loans foreclosed or in default temporarily. Specifically, costs include lost principal, lost interest on principal during the period of litigation and foreclosure, costs in administration, legal fees, insurance coverage and property taxes. Type 2 error occurs when a low-risk borrower is adversely rejected, and the loan is given to alternative borrower. Type 2 error has 3 components. The first is the foregone interest income from adverse rejection of a good loan or low-risk borrower. The second is the interest income obtained in case the alternative borrower is a good borrower, and the third is the lost money in case the alternative borrower is a bad borrower. Losses include the difference in expected profit foregone from the low-risk borrower and the expected profit from the alternative borrower.

Since type 2 error is not observable, it can be argued that rejecting a good loan or low-risk borrower is not very costly. However, under the assumption that the lender will lend the money to an alternative borrower, the cost associated with type 2 error can be high if the alternative borrower has high credit risk. In this situation, the lost revenue from an adversely rejected good loan may not be recoverable and the possible type 1 error due to the alternative borrower being high credit risk but being adversely accepted increases the cost of Type 2 error. In general, the misclassification errors are costly to the lender and they influence the overall profitability of the loan portfolio. Estimating separate credit scoring models for different farm types in the same region will minimize these classification errors.

As mentioned, in general the credit scoring models of lenders do not reflect benchmarks such as farm type. Instead lenders adjust their models to farm types subjectively. However, previous research shows that bankers intend to use less subjective and more quantitative methods. For instance, Featherstone, Roessler, and Barry (2006) state that lenders use statistical rating systems and professional judgment and experience in their rating processes, because lenders believe that professional judgment and experience provide greater accuracy, confidence and flexibility in their rating systems. However, they also state that, with Basel II, lenders started using more advanced rating systems. As lenders improve on their risk-rating systems, they focus more on quantitative assessment rather than subjective methods since quantitative assessment shortens the decision process and gives more standardized results. Hence, quantitative methods such as credit scoring models, which are recently the focus of lenders, are an important tool for bankers.

Turvey and Brown (1990) looked at whether differences in farm types and regions should be accounted for in credit scoring models, but they did not look at what explanatory factors became important across different farm types and regions. The advantage of their study is that they use national data base, resulting in a diverse set of farms. They found that for Canada’s Farm Credit Corporation, farm type played an important role in the development of credit scoring models. However, this has not been analyzed for the US. In US, the lenders service specific regions and are not nationalized. Consequently, most of the credit scoring models are regional. While credit scoring models differ from region to region, lenders tend to use a single credit scoring model for all farm types in that region. For instance Miller and LaDue (1989) developed a credit scoring model for a bank in New York and focused on dairy farms while Luftburrow, Barry and Dixon (1984) developed one credit scoring model for five production credit associations in Illinois, with three of production credit associations focusing on grain farms and the other two association having diverse borrower type such as dairy, beef and hog farms.

Here we investigate the importance of developing different credit scoring models for a specific region in US. This study differs from Turvey and Brown (1990) by determining whether different explanatory factors become important for credit scoring models across livestock farms and crop farms.

Previous research also states that the effect of different farm types on credit scoring models, credit risk migration analysis should be analyzed, as well as on the effect of credit scoring in pricing decisions.  For instance, Splett et al. (1994) stated that lenders should develop credit scoring models based on different structural characteristics such as loan structure, and farm type. Phillips and Katchova (2004) stated that the migration analysis differences could also occur across farm types. Lufburrow, Barry and Dixon (1984) stated that testing the usefulness of credit scoring models in pricing decisions for different farm types might be a good future research.

## III) Data

This paper uses FBFM (Illinois Farm Business Farm Management Association) data for 1995 to 2004, after screening for balance sheet, family living sources and uses, and economic management analysis certifications.  The farmdoc website lists debt-to-asset ratio for different farm types, hog, dairy, beef, and grain farms. For example, for 2004 the median debt to asset ratio for each farm type is 35.9%, 31.6%, 25.3%, and 28.5% sequentially. Based on this, it can be concluded that debt levels vary by farm type. Further, Plumley and Hornbaker (1991) have identified financial management characteristics of both financially successful and less successful farms using FBFM data. Therefore, it can be concluded that there is enough variability in FBFM data to categorize or classify borrowers.

Even though lender data is preferred to analyze credit scoring models, previous studies used farm-level data to proxy for lender data. For instance, Katchova and Barry (2005) analyzed debt-to-asset ratio and inferred about distance to default by FBFM data. Escalante, Barry, Park, and Demir (2004) used FBFM data as a proxy to lender data when analyzing the determinants of credit risk migration rates. Phillips and Katchova (2004) analyzed the credit score migration of farm businesses by FBFM data. Barry, Escalante, and Ellinger (2002) applied credit risk migration analysis to FBFM data.

In order for a loan to be at default, it needs to be past due. A loan becomes past due over a period of time. Lufburrow, Barry and Dixon (1984) state that credit scoring models should reflect the relative performance of the borrowers over a number of years. To reflect this temporal dimension, this study will use data for several years rather than focusing on a specific year. Since FBFM changed its data format, this study uses data from 1995 to 2004. This long range of time is also consistent with previous studies. For instance, Escalante, Barry, Park, Demir (2004) have used FBFM data over a 10 year period to estimate farm-level and macroeconomic determinants of farm credit risk migration rates. Plumley and Hornbaker (1991) have used FBFM data over 4 years to estimate financial management characteristics of successful farms.

This study looks at hog, dairy, beef and grain farm types. The hog data in FBFM only includes those hog family farms which also produce grain to feed their animals, not the hog produced by factory systems, since that requires private data. Although hog farms can produce grain to feed their animals, there is still considerable difference between hog and grain farms. That is, they have different levels of leverage, equity, farm land etc. Due to that, this study considers hog farms and grain farms as different farm types even though hog farms can as well produce grain to feed their animals.

The ratios of return on farm assets and debt to farm operating income[1] which are above or below the mean plus or minus 3 standard deviations are deleted to resolve potential outlier problems.

## IV) Methodology and Model Specification

<u>Theory</u>

This section outlines the theory used. Lenders are interested in maximizing return on a loan or minimizing the expected loss. Katchova and Barry (2005) define expected loss as:

EL= (PD) (LGD) (EAD)

Where EL is the dollar value for expected loss per farm, PD is probability of default (in percentage), LGD is loss given default (in percentage), and EAD is the exposure at default (in dollars). Probability of default (PD) is the frequency of loss and is determined by characteristics of borrowers. Loss given default (LGD) is the severity of loss and is determined by characteristics of transactions. Exposure at default (EAD) is the value of farm debt at the time of default.

Credit risk tries to identify probability of default (PD). Hence, for credit risk purposes, lenders evaluate borrower characteristics which are defined by financial ratios. Therefore, the credit scoring model in this study will look at financial ratios just like other previous studies

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[1] Farm operating income: net income from operations.
For detailed calculation, please see page 55-56 in Barry, P.J., P.N. Ellinger, C.B. Baker, and J.A.Hopkin. 2000. Financial Management in Agriculture. Danville, Illinois: Interstate Publishers, Inc.

(Turvey and Brown, 1990; Turvey, 1991; Barry, Escalante, and Ellinger, 2002; Splett, Barry, Dixon, and Ellinger, 1994).

## Variables

*Dependent variable:*

The differentiation of the dependent variable across classes (lowest to highest risk class) and categories (acceptable or problematic borrowers) will be made via loan repayment. Miller and LaDue (1989) have emphasized that loan repayment is an objective measure. Therefore, dependent variable (either as classes or categories) will be measured by the ability of borrowers to repay the loan. In FBFM data, repayment capacity is defined either by capital replacement and term debt repayment margin, or debt to farm operating income. Since this article deals with different farm types and different farm types might have different sizes, ratios are more appropriate than dollar measures. The ratio of debt to farm operating income, thus serves as the dependent variable.

The dependent variable in this article is discrete rather than continuous. A discrete dependent variable is used rather than continuous dependent variable for the following reason. Lender is interested in which borrowers are likely to default and not default rather than ratios level. Based on debt to farm operating income, borrowers are divided into two categories: acceptable borrowers versus problematic borrowers. Further based on debt to farm operating income, borrowers are assigned across classes; from 1 to 5. Class 1 represents the lowest risk, meaning lowest debt to farm operating income while class 5 represents the highest debt to farm operating income.

A cut-off point is used to categorize between problematic or acceptable borrowers. The cut off is created by the following method.  Problematic borrowers are defined as having ratios of debt to farm operating income that are negative (10% of the observations) or among the highest five percent of the ratio, yielding 15% as problematic borrowers.  As the second criteria for cut off point; above 90% (top 10%) and negative debt to farm operating income was taken as problematic borrowers.  Below 90% and positive debt to farm operating income was taken as acceptable borrowers.

The five classes are created based on the following method.  To assign repayment ability into five classes, the negative debt to farm operating income was deleted since those borrowers had negative income and they were financially stressed and they were the ones who would be very likely to default.  The rest of data was divided based on quartiles and were assigned into classes based on those quartiles. For instance, from negative-0 was deleted, 0-25% was assigned as class 1, 25%-50% was assigned as class 2, 50%-75% was assigned as class 3, 75%-95% was assigned as class 4, above 95% was assigned as class 5.

*Independent variables:*

Among the FBFM data, some financial trend analysis data is provided.  Among those data are the liquidity, solvency, profitability, financial efficiency and repayment capacity analysis.

The liquidity is usually analyzed by working capital and current ratio. However, lenders generally use working capital to value of farm production ratio to analyze liquidity.  Since in this paper, value of farm production is represented by gross farm returns, working capital to gross farm return is taken as independent variable to represent liquidity.

The solvency is analyzed by net worth (market), net worth (modified cost), debt/equity (market), debt/total assets (market). Since each of them are nearly the same and the dependent variable (debt to farm operating income) has debt concept, to prevent multi-colinearity issue, net worth (market) is taken as independent variable rather than debt/equity or debt/total assets.

The profitability is analyzed by net farm income and net non-farm income. These are different measurements for FBFM data because FBFM data involves large farms. Since, small farms rely more on net non-farm income whereas large farms use net farm income, using these two ratios together will not give multi-colinearity problem. Further profitability is analyzed by net income less withdrawals. To calculate this ratio, net farm income and net non-farm income are used together. If net income less withdrawals is used, net farm income and net non-farm income cannot be used. Other than these, profitability is analyzed by return on farm assets (market) and return on farm equity (market). This article will use return on farm assets as independent variable to represent farm profitability.

The financial efficiency is analyzed by interest expense to gross farm returns, operating expense to gross farm returns, depreciation expense to gross farm returns[2], farm operating income to gross farm returns, asset turnover ratio, and net withdrawals/net income. Since there might be positive correlation between depreciation expense, interest expense and operating expense, to prevent multi-colinearity, only one of those ratios will be used. Since farm operating income is calculated from interest, operating and depreciation expense (1 – interest expense- operating expense- depreciation expense), farm operating income to gross farm returns will not be used. To measure financial efficiency, this article will use depreciation expense to gross farm returns for

[2] Starting in 2003, FBFM used economic depreciation instead of tax depreciation. To the extent that different definitions are used for the same variable, the results may be affected.

livestock farms and operating expense to gross farm returns for crop farms. As a second measurement of financial efficiency, this paper will take asset turnover ratio.

Therefore, as independent variables, the following categories are established: liquidity, solvency, profitability, and financial efficiency. These categories are measured by working capital to gross farm return(WCGFR), net worth (NW), return on farm assets (ROFA), operating expense to gross farm return (OEGFR) or depreciation expense to gross farm return (DEGFR), and asset turnover ratio (ATR). These measurements are chosen to minimize multi-colinearity between them and to exclude debt since dependent variable (acceptable borrower or moving into a lower risk class) includes debt in its measurement. Tables 1 and 2 give detailed information regarding these independent variables. Further, detailed information is provided regarding how these variables are measured and their expected signs with borrower being acceptable or borrower being assigned into lower risk class.

In Table 1, it is seen that OEGFR is not considered for Livestock category, because of multi-colinearity between ROFA and OEGFR. Since across categories and classes, borrowers have different mean measures for ROFA and similar mean measures for OEGFR, this means OEGFR variable does not differentiate between acceptable and problematic borrowers or borrowers across classes, as well as ROFA does. Because of this ROFA was used and OEGFR was replaced with an alternative measure DEGFR. OEGFR is not replaced with interest expense/gross farm return because this is also related with dependent variable. There was no multi-colinearity between ROFA and DEGFR even though higher depreciation ratio would be associated with lower ROFA.

The expected sign for WCGFR is positive. Working capital to gross farm returns, relates the amount of working capital to the size of operation. The higher the ratio, the more liquidity the farm operation has, to meet current obligations. As more liquidity the farm operation has, the more acceptable it becomes as a borrower and the more probable it belongs to a lower risk class.

The expected sign for NW is positive. Net worth measures the solvency of the farm. As net worth increases, the higher solvency the farm has and the more acceptable it becomes as a borrower and the more probable it is in a lower risk class.

However, for crop farms when WCGFR, NW, ROFA, OEGFR, ATR are regressed without tenure included; NW has negative sign under both 95% cut off and 90% cut off which is different than what is expected, while across classes NW is not significant. For livestock farms, across categories and classes, NW is not significant, as well. The reason, NW sign is different than what is expected might be due to Tenure effect. As NW increases, the farmers tend to be wealthier and they own more. As landownership increases, tenure increases. Therefore, high NW could be associated with high tenure. With high net worth and tenure (increased landownership), there is lower leverage, less liquidity, a lower current rate of return on assets, and a greater portion of the borrower's economic rate of return occurring as unrealized capital gains on farm land. Thus tenure and net worth can combine to show a lower repayment capacity for the following reason. Since rate of return on assets is: (current cash rate of return+ change in value of asset) / total assets; as NW and tenure increase, the lower current rate of return on assets means the current cash rate of return increases less compared to the increase in value of asset. Therefore, there is high capital gains and low cash flow. There is not enough cash generated to pay back debt if debt relative to farm income is high. That is why as NW and tenure increase, the farm owners become financially infeasible and they are less likely to be assigned to lower risk class. Therefore, the expected sign of NW becomes negative when level of net worth and level of leverage (debt to farm operating income) interact with tenure (land ownership).

Tenure is added as independent variable to crop farms since it has effect on level of leverage and the decision to categorize borrowers as acceptable or problematic and the decision to assign borrowers across classes.  The mean of tenure ratio for livestock farms is greater than crop farms (36.3% and 23.9% respectively).  The livestock farms still have extensive crop operations and rely heavily on leasing with a tenure ratio of 36.3%, indicating that about 63.7% of their acreage is leased.  Not surprisingly, the mean tenure ratio for crop farms is as well low at 23.9%. Since, livestock farms have higher tenure ratio than crop farms, it is reasonable to add tenure variable into the livestock farms as well. Therefore, in conclusion, both farm types have tenure variable included into independent variables.

The expected sign of tenure ratio is negative since as tenure increases, there is not enough cash generated to pay back debt if high debt relative to farm income is taken. Therefore, borrowers become less acceptable and less likely to be assigned into lower risk class, with an increase in tenure ratio.

The expected sign of return on farm assets is positive.  Return on farm assets, measures the pretax rate of return on farm assets and can be used to measure the effective utilization of assets on the profitability of the business. As this ratio is higher, the more effective utilization of assets and the more acceptable the farmer becomes as a borrower and the more likely the borrower belong to lower risk class.

The expected sign of operating expense to gross farm return is negative.  Operating expense to gross farm return; measures the farm's efficiency of operating expense management. As this ratio is higher, the higher the total operating expenses are and the lower the farm's efficiency is with respect to operating expense management. Therefore, the less acceptable the farmer becomes as a borrower and the less likely the borrower belongs to lower risk class.

The expected sign of depreciation expense to gross farm return is negative. As this ratio is higher, the higher the depreciation expense is and lower efficiency farm has in depreciation expense management. Therefore, the less acceptable the farmer becomes as a borrower and the less likely the borrower belongs to lower risk class.

The expected sign of asset turnover ratio is positive. Asset turnover ratio is a general measure of farm's efficiency of asset utilization. The higher this ratio is, the more effectively assets are used to generate revenue. Therefore, the more acceptable the farmer becomes as a borrower and the more likely the borrower belongs to lower risk class.

Statistical approach used to develop credit scoring model:

LOGIT is used for the following reason. According to Miller and LaDue (1989) discriminant analysis is not proper for financial ratio measures since financial ratios are not normally distributed and discriminant analysis assumes normal distribution. Further, according to Turvey (1991), prediction accuracy of discriminant analysis is the highest. Following it are LOGIT, PROBIT, linear probability model, in sequence. Since this article deals with financial ratios and financial ratios are not normally distributed, LOGIT is used which has the next highest prediction accuracy, after discriminant analysis.

Three types of regression are done for each farm type (livestock and crop farms). Two of those regressions involve the case where dependent variable is determined across categories by using 95% cut off and 90% cut off. The third regression involves the case where dependent variable is determined across five credit risk classes.

**Regression Results**

<u>Descriptive Statistics</u>

Tables 3 and 4 indicate the following relationships in the mean analysis of independent variables and dependent variable. For both farm types, debt to farm operating income is higher for acceptable borrowers compared to problematic borrowers. This is logical considering how we created the category of problematic borrowers. For problematic borrowers, negative DFOI is taken as well as the highest DFOI ratios. Due to negative DFOI, the mean of this ratio is lower for problematic borrowers compared to acceptable borrowers. Across classes, the mean of DFOI is increasing as borrower risk increases. This is logical since low DFOI means low debt and low risk. This is also consistent with how the classes are created since all positive DFOI was assigned into five risk classes depending on the magnitude of DFOI.

For both farm types, the mean for WCGFR, ROFA, and ATR are greater for acceptable borrowers compared to problematic borrowers and for lowest risk class compared to highest risk class. For both farm types, the NW is higher for acceptable borrowers compared to problematic borrowers. However, it is harder to say the same trend for changes of mean in NW across classes. Both farm types have U-shaped patterns in the means of NW across five risk classes (ie: higher at both ends and lower toward the middle risk class).

For both farm types; the mean for OEGFR, DEGFR, and Tenure ratio are lower for acceptable borrowers compared to problematic borrowers. For livestock farms, DEGFR follows a U-shaped pattern whereas tenure ratio increases with higher risk classes, as expected. For crop farms, Tenure ratio follows a U-shaped pattern across classes, while OEGFR increases with higher risk classes, as expected.

Regression Results

The results presented in Tables 5 and 6 are informative across the risk groups and farm types. Mostly the significance or the lack of significance of the variables matches well with the changes in means across classes and groups. Numerous variables are significant and have signs as expected except for Tenure ratio for livestock farms for 90% cut off and NW for crop farms across classes. Before adding tenure, for crop farms net worth was significant but without the expected sign, while for livestock farms net worth was insignificant. Adding tenure made the sign of NW as expected for 95% cut off and 90% cut off for crop farms whereas adding tenure did not have any impact on the significance of NW for livestock farms.

For livestock farms; WCGFR, ROFA, DEGFR, ATR are all significant within 5% of significance level for 95% cut off, 90% cut off, and across classes. These ratios, thus, can be used to categorize borrowers into either acceptable or problematic. These results will be robust even if different cut off points are used to describe borrowers as acceptable or problematic. Further these ratios can be used as well to classify borrowers across classes. Further, their signs are as expected. As WCGFR, ROFA, ATR increase, the borrower is more likely to be acceptable and more likely to be assigned into a lower risk class. As DEGFR increases, the borrower is less likely to be acceptable and less likely to be assigned into lower risk class.

NW is not significant for 95% cut off, 90% cut off, and across classes. That means NW does not play significant role in livestock farms, to define borrowers as acceptable or problematic and to assign borrowers into different risk classes.

Tenure ratio is significant for 90% cut off under 10% significance level and has sign different than what is expected, whereas insignificant for 95% cut off, and across classes. The reason for having sign different than expected might be that since livestock farms make investments in the buildings, feed livestock and at the same time still have extensive crop operations, ownership of land is more important for livestock farms. Further, as the mean of tenure ratio shows, livestock farms (hog, dairy and beef) own relatively more land compared to crop farms. This high ownership of land is viewed more favorably for livestock farms since it gives them stability. However, this stability reduces the impact of the explanation given above for the expected negative sign for tenure variable. Further, tenure ratio is sensitive to description of acceptable or problematic borrowers based on cut off points. With different cut off points used, tenure ratio might be significantly important or not important in determining the creditworthiness of a borrower. However, if borrower is defined across classes, tenure ratio will have no significant effect.

For crop farms; WCGFR, NW, ROFA, OEGFR, ATR, and Tenure ratios are all significant across categories for 95% cut off, 90% cut off, and across classes. This shows that for crop farms, all of these ratios play significant role in determining whether a borrower is acceptable or not and it does not matter which cut off is taken to determine the dependent variable. The results are robust with different cut off points such as 95% and 90%. Further all of these ratios play significant role in assigning borrower across classes.

The signs of WCGFR, ROFA, and ATR are as expected. As these ratios increase, the borrower is more likely to be acceptable and the borrower is more likely to be assigned into a lower risk class. The signs of OEGFR and tenure are as expected as well. As they increase, the borrower is less likely to be acceptable and borrower is less likely to be assigned into a lower risk class.

The sign of NW is as expected for determining whether a borrower is acceptable or problematic. As it increases, the borrower is less likely to be acceptable. However, for assigning into different classes, NW is significant only with 10% significance level and its sign is opposite of expectation. As NW increases, the borrower will more likely be assigned into lower risk class.

<u>% correctly and mistakenly predicted:</u>

As can be seen in Table 5: for livestock farms, with 95% cut off point; the model can predict correctly the borrower type (whether it is acceptable or problematic) 95.5% of the time, whereas with 90% cut off point, this correctly predicted percentage is 94.2% and with five different risk classes, this percentage decreases to 76.2%. Percentage correctly predicted is higher for two borrower types compared to five borrower types. As can be seen, assigning the borrowers into five different risk classes increased the percentage of borrowers that have been mistakenly predicted and the model mistakenly predicts 23.5% of the time the riskiness class the borrower belongs to. The efficiency of the model decreases with higher number of borrower types. This is consistent with Barry, Escalante, and Ellinger (2002).

The same trend can be seen with crop farms in Table 6. For crop farms, the percentage of borrowers being correctly classified reduces as the borrower types increase from two type to five type. The 95% cut off predicts better whether a borrower is acceptable or not compared to 90% cut off, and five different risk classes. However, there is not too much difference between what 95% cut off predicts and 90% cut off predicts; 94.5%, 93.2% respectively. There is more difference in the percentage correctly predicted for five borrower types and two borrower types: 83.4%, 94.5%, 93.2% respectively across classes, and 95% cut off, 90% cut off across categories.

Significance of intercept:

For livestock farms; intercept is insignificant for 95% cut off across categories. This means that there is no difference between borrower being acceptable or problematic with effects of independent variable considered. The two categories are nearly the same. For 90% cut off across categories, intercept is significant. Therefore, there is difference between borrowers being acceptable or problematic even after controlling with several independent variables. The two categories represent different borrower types. Across classes, all intercepts are significant. That means lowest risk class is different than low risk class, low risk class is different than medium risk class, medium risk class is different than high risk class and high risk class is different than highest risk class. Different classes represent different borrower types.

For crop farms; 95% and 90% cut off across categories, intercept is significant. Therefore, there is difference between borrower being acceptable or problematic. The two categories are not the same. Across classes, all intercepts are significant. Different classes represent different borrower types.

## Summary and Conclusions

In conclusion, this article analyzed whether credit scoring models differ across livestock farms and crop farms. As dependent variable, repayment capacity is used since it is an objective way of measurement. Repayment capacity is measured by debt to farm operating income. This dependent variable is categorized under 95% cut off, 90 % cut off, and across five credit risk classes. The independent variables are tenure, liquidity, solvency, profitability, and financial efficiency. These categories are measured by tenure, working capital to gross farm return (WCGFR), net worth (NW), return on farm assets (ROFA), operating expense to gross farm return

(OEGFR) for crop farms or depreciation expense to gross farm return (DEGFR) for livestock farms, and asset turnover ratio (ATR). Since, financial ratios are not normally distributed and discriminant analysis assumes normal distribution; as statistical method LOGIT is used which has the next highest prediction accuracy after discriminant analysis.

The following results are obtained for livestock farms and crop farms. For livestock farms; liquidity, profitability, financial efficiency play significant role in assigning borrowers across classes and categories, no matter what the cut off point is. However, solvency plays no significant role to assign borrowers across categories or classes. The tenure ratio is sensitive to the cut off point used for assigning borrowers into categories. With 90% cut off, tenure ratio is significant but its sign is different than what is expected. Tenure ratio does not play any significant role to assign borrowers into classes.

For crop farms; liquidity, profitability, financial efficiency, and tenure ratio all play significant role in assigning borrowers across categories and classes. Solvency is also significantly important while assigning borrowers across classes and categories.

When the borrower type is small (when borrower is categorized into two types either acceptable or problematic), the model is predicted more accurately compared to higher number of borrower type (five risk classes).

95% cut off better predicts the model compared to 90% cut off and five classes when we look at percent concordant. However, for livestock farms; the 95% cut off fails in distinguishing between acceptable borrower and problematic borrower when we look at the significance of intercept.

A major conclusion drawn from these results is that multiple models are needed, separately for livestock and crop farms, differing primarily in significance of the solvency and tenure variables. Using the same model across multiple farm types would yield less accurate results.

To check for the robustness of this paper, the same model can be analyzed for different number of classes such as three classes, seven classes etc. Further, this paper can be enhanced by changing the way classes are created. Further, the same model can be applied to livestock farms without including tenure while including tenure for crop farms, since tenure was added to see how the sign of net worth changes for crop farms.

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**Table 1. Variable Definitions and Expected Signs for Livestock Farms (Tenure Variable included)**

| Category | Variable | Definitions | Expected Sign in regards to Acceptable Borrower |
|---|---|---|---|
| Repayment Capacity | (DFOI) Debt to Farm Operating Income | Debt / Farm Operating Income | |
| Liquidity | (WCGFR) Working Capital to Gross Farm Returns | (Current Assets - Current Liabilities) / Gross Farm Returns | (+) |
| Solvency | (NW) Net Worth (market) | Fair Market Value of Farm Assets - Fair Market Value of Farm Liabilities | (-) |
| Profitability | (ROFA) Return on Farm Assets (market) | (Net Farm Income from Operations + Farm Interest Payments - Unpaid Labor Charge for Operator and Family) / (Average Total Farm Assets in fair market value) | (+) |
| Financial Efficiency | (DEGFR) Depreciation Expense to Gross Farm Return | Total Farm Depreciation / Gross Farm Returns | (-) |
| | (ATR) Asset Turnover Ratio | Value of Farm Production / Total Average Farm Assets (fair market value) | (+) |
| Tenure | (Tenure) Tenure | Owned Acres / Total Acres Operated | (-) |

**Table 2. Variable Definitions and Expected Signs for Crop Farms (Tenure Variable Included)**

| Category | Variable | Definitions | Expected Sign in regards to Acceptable Borrower |
|---|---|---|---|
| Repayment Capacity | (DFOI) Debt to Farm Operating Income | Debt / Farm Operating Income | |
| Liquidity | (WCGFR) Working Capital to Gross Farm Returns | (Current Assets - Current Liabilities) / Gross Farm Returns | (+) |
| Solvency | (NW) Net Worth (market) | Fair Market Value of Farm Assets - Fair Market Value of Farm Liabilities | (-) |
| Profitability | (ROFA) Return on Farm Assets (market) | (Net Farm Income from Operations + Farm Interest Payments - Unpaid Labor Charge for Operator and Family) / (Average Total Farm Assets in fair market value) | (+) |
| Financial Efficiency | (OEGFR) Operating Expense to Gross Farm Return | (Total Operating Expenses - Depreciation) / Gross Farm Returns | (-) |
| | (ATR) Asset Turnover Ratio | Value of Farm Production / Total Average Farm Assets (fair market value) | (+) |
| Tenure | (Tenure) Tenure | Owned Acres / Total Acres Operated | (-) |

**Table 3. Mean Values for Livestock Farms**

| | | 95% cutoff in DFOI | | 90% cut off in DFOI | | Classes in DFOI | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | All | Acceptable Borrower | Problematic Borrower | Acceptable Borrower | Problematic Borrower | Lowest Risk | Low Risk | Medium Risk | High Risk | Highest Risk |
| Debt to farm operating income | 4.863 | 6.373 | -0.199 | 5.149 | 4.100 | 0.692 | 2.839 | 6.080 | 16.674 | 99.343 |
| Working capital to gross farm return | 0.380 | 0.457 | 0.120 | 0.469 | 0.141 | 0.912 | 0.488 | 0.264 | 0.297 | 0.188 |
| Net worth | 820,670 | 844,171 | 741,907 | 842,240 | 763,239 | 1,047,591 | 846,256 | 722,267 | 838,141 | 802,864 |
| Return on farm assets | 0.054 | 0.080 | -0.034 | 0.083 | -0.024 | 0.092 | 0.102 | 0.080 | 0.037 | 0.017 |
| Asset turnover ratio | 0.318 | 0.340 | 0.243 | 0.346 | 0.242 | 0.345 | 0.368 | 0.370 | 0.254 | 0.290 |
| Depreciation expense to gross farm return | 0.093 | 0.075 | 0.155 | 0.073 | 0.146 | 0.083 | 0.060 | 0.068 | 0.098 | 0.136 |
| Tenure ratio | 0.363 | 0.357 | 0.381 | 0.358 | 0.376 | 0.345 | 0.350 | 0.352 | 0.387 | 0.393 |
| Observations | 879 | 677 | 202 | 639 | 240 | 122 | 210 | 200 | 145 | 49 |

**Table 4. Mean Values for Crop Farms**

| | | 95% Cut Off in DFOI | | 90% Cut Off in DFOI | | Classes in DFOI | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | All | Acceptable Borrower | Problematic Borrower | Acceptable Borrower | Problematic Borrower | Lowest Risk | Low Risk | Medium Risk | High Risk | Highest Risk |
| Debt to farm operating income | 4.126 | 6.730 | -9.734 | 5.496 | -1.053 | 0.770 | 2.844 | 6.187 | 16.226 | 128.292 |
| Working capital to gross farm return | 0.442 | 0.501 | 0.126 | 0.529 | 0.113 | 1.399 | 0.541 | 0.278 | 0.131 | 0.106 |
| Net worth | 821,714 | 832,391 | 764,887 | 838,904 | 756,721 | 1,097,219 | 839,635 | 738,984 | 762,718 | 813,630 |
| Return on farm assets | 0.052 | 0.066 | -0.021 | 0.069 | -0.012 | 0.075 | 0.093 | 0.063 | 0.031 | 0.007 |
| Asset turnover ratio | 0.345 | 0.355 | 0.288 | 0.359 | 0.290 | 0.323 | 0.394 | 0.363 | 0.318 | 0.279 |
| Operating expense to gross farm return | 0.631 | 0.601 | 0.788 | 0.596 | 0.762 | 0.554 | 0.569 | 0.611 | 0.660 | 0.710 |
| Tenure ratio | 0.239 | 0.234 | 0.263 | 0.232 | 0.265 | 0.274 | 0.214 | 0.212 | 0.260 | 0.306 |
| Observations | 7,530 | 6,339 | 1,191 | 5,955 | 1,575 | 1,019 | 1,893 | 1,902 | 1,526 | 374 |

**Table 5. Logit Results for Livestock Farms**

| Variables | 95% Cut Off[a] | 90% Cut Off[b] | Classes[c] |
|---|---|---|---|
| Intercept 1 | -0.1289 | -1.1167 | -4.3495 |
| | (0.4676) | (0.4302)** | (0.3127)** |
| Intercept 2 | | | -2.4513 |
| | | | (0.2797)** |
| Intercept 3 | | | -0.8668 |
| | | | (0.2683)** |
| Intercept 4 | | | 1.0918 |
| | | | (0.2875)** |
| Working capital to gross farm return | 2.022 | 1.96 | 2.0008 |
| | (0.2887)** | (0.2632)** | (0.1646)** |
| Net worth | -0.000000194 | -0.000000225 | -0.000000002 |
| | (2.377E-7) | (2.11E-7) | (1.247E-7) |
| Return on farm assets | 46.4815 | 40.8448 | 12.7758 |
| | (4.1478)** | (3.4987)** | (1.3781)** |
| Depreciation expense to gross farm return | -6.62 | -4.8946 | -2.6121 |
| | (1.7218)** | (1.5705)** | (1.0614)** |
| Asset turnover ratio | 2.617 | 3.1068 | 1.2412 |
| | (0.9203)** | (0.8216)** | (0.4507)** |
| Tenure ratio | 0.2543 | 0.7813 | 0.3906 |
| | (0.4919) | (0.4511)* | (0.2617) |
| Number of observations | 879 | 879 | 726 |
| Log L (intercept only) | -473.8185 | -515.3195 | -1,101.59 |
| Likelihood Ratio | (552.7853)** | (556.7957)** | (305.3367)** |
| Score | (382.9782)** | (384.6812)** | (238.5193)** |
| Wald | (148.9685)** | (168.7452)** | (260.1947)** |
| Percent Concordant | 95.5 | 94.2 | 76.2 |
| Percent Discordant | 4.4 | 5.7 | 23.5 |

Note: Standard errors are in parentheses and **, and * denote significance at 5% and 10%, respectively, and dependent variable is borrower being acceptable.

Note:borrower=1 represents acceptable borrower, borrower=0 represents problematic borrower.

[a]The borrower is acceptable based on the 95% cut off.

[b]The borrower is acceptable based on the 90% cut off.

[c]The borrower is divided into 5 classes with 5 representing the highest risky class.

**Table 6. Logit Results for Crop Farms**

| Variables | 95% Cut Off[a] | 90% Cut Off[b] | Classes[c] |
|---|---|---|---|
| Intercept 1 | 6.8988 | 5.3721 | -1.6195 |
| | (0.4023)** | (0.3452)** | (0.1849)** |
| Intercept 2 | | | 0.7034 |
| | | | (0.1823)** |
| Intercept 3 | | | 2.605 |
| | | | (0.1852)** |
| Intercept 4 | | | 5.1362 |
| | | | (0.1959)** |
| Working capital to gross farm return | 1.4027 | 1.6755 | 2.3882 |
| | (0.0891)** | (0.0860)** | (0.0544)** |
| Net worth | -0.00000023 | -0.000000137 | 6.762E-08 |
| | (6.957E-8)** | (6.335E-8)** | (4.026E-8)* |
| Return on farm assets | 36.2858 | 32.9085 | 13.871 |
| | (1.6264)** | (1.3885)** | (0.5650)** |
| Operating expense to gross farm return | -9.4895 | -8.4501 | -5.4182 |
| | (0.5440)** | (0.4777)** | (0.2736)** |
| Asset turnover ratio | 2.3441 | 2.1833 | 1.0752 |
| | (0.2703)** | (0.2389)** | (0.1296)** |
| Tenure ratio | -0.9159 | -0.8432 | -0.6009 |
| | (0.1898)** | (0.1737)** | (0.1134)** |
| Number of observations | 7,530 | 7,530 | 6,714 |
| Log L (intercept only) | -3,287.7365 | -3,861.7310 | -10,057.6005 |
| Likelihood Ratio | (3,468.3434)** | (3,819.2782)** | (4,527.8684)** |
| Score | (2,620.2321)** | (2,771.5236)** | (2,779.3175)** |
| Wald | (1,176.4132)** | (1,376.3982)** | (3,170.6801)** |
| Percent Concordant | 94.5 | 93.2 | 83.4 |
| Percent Discordant | 5.3 | 6.6 | 16.4 |

Note: Standard errors are in parentheses and **, and * denote significance at 5% and 10%, respectively, and dependent variable is borrower being acceptable.

Note:borrower=1 represents acceptable borrower, borrower=0 represents problematic borrower.

[a]The borrower is acceptable based on the 95% cut off.

[b]The borrower is acceptable based on the 90% cut off.

[c]The borrower is divided into 5 classes with 5 representing the highest risky class.