Credit Scoring Models in Illinois by Farm Type: Hog, Dairy, Beef and Grain

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Abstract

Employing a logit model and farm-level data for Illinois from 1995 to 2004, this study explores the importance of farm-type differences in the development of credit scoring models. Apart from the conclusion that regional credit scoring models specific to each farm type are needed, the following are identified as the most pertinent factors for explaining creditworthiness: previous year's working capital to gross farm return, the debt-to-asset ratio, and return on farm assets. Furthermore, beef farms have a larger marginal effect compared to grain farms on the probability of the farmer being highly creditworthy. Hog farms differ from grain farms in how the following financial characteristics affect farmer creditworthiness: solvency, profitability, and financial efficiency. These separate credit scoring models result in increased expected profit for the lender, better capital management, less bankruptcy, and less burden on the government and tax payers.

Key words: creditworthiness, credit scoring, cut-off point, farm type, FBFM

I. Introduction

The Farm Credit System (FCS), which is the major lender of agricultural loans, typically issues five different aggregate types of loans: commercial farm, farm real estate, agribusiness, rural housing, and small loans. Although the FCS groups loan applications into the categories above and treats them differently, the institution does not specifically account in its quantitative analysis for differences due to farm types. Analysis of data collected from the Illinois Farm Business Farm Management (FBFM) Association shows that financial characteristics across hog, dairy, beef and grain farms differ in Illinois.

When the FCS considers a loan application, it treats an application from the hog industry in exactly the same way as an application from the dairy industry. In reality, considerable differences in rates of return on assets, leverage ratios and liquidity exist among different agricultural enterprises.[1] For example, Boessen, Featherstone, Langemeier, and Burton (1990) identify large differences between the return on assets and leverage ratios for swine farms and beef cow farms. The return on assets for swine farms is three times greater than the return on assets for beef farms. Furthermore, swine farms have a leverage ratio of 0.25 compared to 0.16 for beef farms.

Even though the FCS does not account quantitatively for differences in farm type, there is some evidence in the literature that the FCS subjectively accounts for such differences but is now moving towards less subjective and more quantitative methods (Featherstone, Roessler, and Barry; 2006). Two objectives of this research are to 1) econometrically confirm whether credit scoring models should differ across hog, dairy, beef and grain farms in Illinois and 2) clarify whether the same set of explanatory variables is relevant for each farm type in Illinois and, if so, whether the marginal effects

[1] Leverage ratio is equivalent to the debt-to-equity ratio.

are identical in magnitude and sign. If differences in explanatory variables exist across farm types, the FCS may need to develop a specific model for each particular farm type.

The FCS does recognize regional differences by using region-specific models. In other words, since a model designed for one region does not necessarily work for another region, the FCS built a model for each region. The problem is that each regional model does not account quantitatively for differences in farm type. Each region has a single credit scoring model, which is typically representative of the farm type dominant in that region. For instance, Miller and LaDue (1989) develop a single credit scoring model for a bank in New York that applies to dairy farms. Luftburrow, Barry and Dixon (1984) develop a single 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 regional scoring models that account quantitatively for differences in farm types has not been developed in the U.S., regional models in Canada do account for such differences. Turvey and Brown (1990) find that for Canada's Farm Credit Corporation, both farm type and region play an important role in the development of credit scoring models.

While regional credit scoring models that account for farm type have not been developed in the U.S., the current literature does suggest that the effect of different farm types on credit scoring models, credit risk migration analysis and pricing decisions deserves further investigation. For instance, Splett, Barry, Dixon, and Ellinger (1994) mention that lenders should develop credit scoring models based on different structural characteristics, such as loan structure and farm type. Phillips and Katchova (2004) argue that for each regional model and each farm type, the migration of farmers from one risk class to another warrants examination. Lufburrow, Barry and Dixon (1984) conclude that testing the usefulness of credit scoring models in pricing decisions for different farm types is worthwhile research.

Improved regional credit scoring models across farm types has the potential to reduce the costs of misclassification, increasing lenders' expected profits. Furthermore, using regional models specific to farm types may provide more equitable treatment of alternative farm types, risk-adjusted pricing across farm types, and greater efficiency in credit evaluation. With more efficient credit evaluation, lenders can more effectively differentiate borrower types. If lenders cannot correctly differentiate between nonperforming and performing loans *ex ante*, the allocation of loan-loss-allowances and capital may not be efficient and unexpected losses might increase resulting in bankruptcy, *ex post*. More efficient credit evaluation results in better capital management, reduced bankruptcy rates, and a lower risk burden borne by the government and tax payers.

II. Literature Review

Considering regional scoring models that control for farm type improves the efficiency of existing credit evaluation models. Improved scoring models effectively differentiate between nonperforming loans and performing loans, thereby reducing misclassification errors. Nayak and Turvey (1997) group misclassification errors into two main types, referred to as type I and type II errors. Type I error occurs when a bad borrower is mistakenly accepted as a good borrower. The costs of this type of error include lost principal, lost interest on principal during the period of litigation and foreclosure, administration costs, legal fees, insurance coverage, and property taxes. By contrast, type II error occurs when a low risk borrower who should be accepted is rejected. The cost component of type II errors includes foregone interest income from rejection of a good loan. Under the assumption that the lender lends the money to an alternative higher-risk borrower, the cost associated with type II error can be prohibitively high.

To analyze the effect of misclassification costs on the overall profitability of lenders, Nayak and Turvey (1997) use data provided by the Farm Credit Corporation of Canada. They compare a logit model, which does not account for misclassification costs, to a cost minimization model, which is developed by incorporating misclassification costs in the credit scoring analysis. Nayak and Turvey find that the lenders' expected profit per dollar lent is $0.0328 in the cost minimization model versus $0.0158 in the logit model, with a difference of $0.017. This difference means that for a $326,277,000 loan, a lender realizes an additional expected profit of $5.5 million, if the cost minimization model is used. Hence, the cost minimization model (which incorporates misclassification costs) outperforms the logit model (which does not incorporate misclassifications) resulting in more accurate loan classification, reduced misclassification costs and increased lender profits.

Turvey and Brown (1990) find that for Canada's Farm Credit Corporation, farm type and region play an important role in the structure of applicable credit scoring models. The advantage of their study is the use of a national database, resulting in a diverse set of farms. In order to account for differences across farm types and regions, dummy variables are used. However, interactions of dummy variables with the explanatory measures are not accounted. In other words, Turvey and Brown make no attempt to isolate which variables are most important given a particular farm type. Different than Turvey and Brown, this paper attempts to identify, for each regional model (specifically credit scoring models for Illinois), the most pertinent variables given a particular farm type (hog, dairy, beef and grain).

Although the role of farm type in credit scoring models has been analyzed for Canadian scoring models, the analysis has not been extended to U.S. models. In the U.S., lenders tend to be localized in specific regions and rarely service the entire country. Consequently, most of the credit scoring models are regional. For instance, a model designed for Illinois is different compared to a model designed for another region. While these credit scoring models consider characteristics specific to a region, they fail to account quantitatively for differences in farm types.

III. Model Specification

This paper analyzes credit scoring models from the perspective of agricultural lenders. While making decisions, lenders are interested in maximizing their expected profit:

$E(\Pi) = (1\text{-}PD)(1+r)(L) + PD((1+r)L\text{-}LGD)$,

where

Π = profit,

L = loan amount,

r = interest rate,

PD = probability of default, which is the frequency of loss, and

LGD = loss given default, which is the severity of loss.

The probability of default is affected by choices and attributes of borrowers. If default occurs, losses arise and the expected profit of the lender decreases. Creditworthiness is an indicator of probability of default. Hence, this paper focuses on the repayment capacity of farmers to understand their creditworthiness.

When analyzing credit scoring models, one issue to consider is whether to run separate regressions for each farm type or to pool the data. Since the FBFM data contain few observations for hog, dairy and beef farms compared to grain farms, the data is pooled and a single equation is used to estimate the different factors across farm types. Dummy variables for farm types are then included to control for farm-type effects. The interaction of the farm-type dummy variables with explanatory variables is used to control for farm-characteristic effects on creditworthiness that change across farm types. Furthermore, dummy variables for years are included to control for factors that are common across farm types but change over time.

To account for the volatility of income, lenders often average income over multiple years. While averaging data smoothes the individual observations and the volatility of income, it reduces the number of observations. Since few observations exist for hog, dairy and beef farms, the data are not averaged.

Following Miller and LaDue (1989) and due to the fact that lenders use current information to evaluate whether a farmer remains creditworthy in the next period, this research uses one year lagged values as explanatory variables. Note that the lagging process eliminates the 1995 observation since it is the first observation. Using 2004 as the base year and grain as the base farm type, the following model is employed:

$$Y_t = \beta_0 + \sum_{i=1}^{i=5} ß_i X_{i,(t-1)} + \text{dummy } j + \text{dummy } k + \sum_{i=1}^{i=5} ß_{ji} \text{ dummy } j * X_{i,(t-1)},$$

where

t = 1996, 1997, …, 2004,

Y_t = classification or categorization based on coverage ratio,

$X_{1,(t-1)}$ = working capital to gross farm return,

$X_{2,(t-1)}$ = debt-to-asset ratio,

$X_{3,(t-1)}$ = return on farm assets,

$X_{4,(t-1)}$ = asset turnover,

$X_{5,(t-1)}$ = tenure,

Dummy j refers to farm type dummy, and grain is the base farm type for this study, and dummy k is the time dummy where k refers to 1996, 1997, …, and 2003.

A possible critique of the model is the use of the coverage ratio as a proxy for creditworthiness (dependent variable) because of possible weak correlation between this financial ratio and creditworthiness. However, Zech and Pederson (2003) obtain reasonable estimates using the coverage ratio as the dependent variable.

In order to apply the logit model, the coverage ratio, which is continuous, must be transformed into discrete form. However, this transformation creates loss of information. Applying the logit model to the transformed variables does not underperform models where original continuous variables are used (Zech and Pederson, 2003; Novak and LaDue, 1997). Thus, this study applies the logit model, which is a common and widely accepted technique cited in previous literature (Turvey and Brown, 1990; Miller and LaDue, 1989; Zech and Pederson, 2003).

Dependent variable:

The dependent variable, the coverage ratio, is a measure of creditworthiness. In general, default oriented and bank examiner classification methods are used to define and measure creditworthiness. The problem with these classification methods is that they can be influenced by subjective behaviors of lenders and borrowers. An alternative measure of creditworthiness is the use of debt repayment capacity derived from the coverage ratio (Novak and LaDue, 1994; Novak and LaDue, 1997). As repayment ability increases, the creditworthiness of farmers is expected to increase. Novak and LaDue (1997) conclude that the coverage ratio may be a meaningful measure of creditworthiness *ex ante*.[2] Since the coverage ratio measures the ability to meet cash obligations, the farmer's creditworthiness improves as this ratio increases. Based on Novak and LaDue (1997), this paper uses the coverage ratio, which is a Farm Financial Standards Council (FFSC-1997) recommended ratio measure for repayment ability, as a measure of the dependent variable. The coverage ratio has several unique properties. It focuses on the basic characteristic of a creditworthy farmer, and the ability to make debt payments based on income. The drawback is the inability to distinguish between variations in profitability and debt levels. For instance, a large (small) coverage ratio may indicate a more (less) profitable or low (highly) leveraged farmer (Zech and Pederson, 2003; Novak and LaDue, 1997).[3]

Since lenders are interested in screening highly leveraged farmers from good farmers, they employ a number of classification schemes. For example, based on the

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[2] Coverage ratio = cash inflow / cash outflow
Cash inflow = net farm income from operations + nonfarm income + depreciation + interest on term debt + interest on capital – income taxes – family living withdrawals.
Cash outflow = annual scheduled principal + interest payments on term debt and capital leases.
[3] Note that a negative coverage ratio also indicates less profitable or highly leveraged farmers.

coverage ratio, a farmer may either be labeled highly creditworthy (one who has very low credit risk) or less creditworthy (one who has higher credit risk) (Zech and Pederson, 2003). A coverage ratio less than 1 indicates that a business may need to increase open-account-balances, borrow additional money, or sell assets in order to meet debt obligations. Thus, a low coverage ratio represents higher credit risk (Zech and Pederson, 2003). Therefore, this study uses 1 as the cut-off point to distinguish between highly creditworthy and less creditworthy farmers.[4]

Explanatory variables:

This paper uses financial ratios as explanatory variables because lenders evaluate farmers' creditworthiness through financial performance measures. Previous studies support the use of financial ratios in credit scoring models (Turvey and Brown, 1990; Turvey, 1991; Barry, Escalante, and Ellinger, 2002; Splett, Barry, Dixon, and Ellinger, 1994). A different set of explanatory variables are used in each credit scoring model (Oltmans, 1994). Based on Miller and LaDue (1989), the following FFSC recommended financial measurements are evaluated: liquidity, solvency, profitability and efficiency to determine the overall creditworthiness of borrowers. Table 1 lists the variables used to measure these factors and their expected signs with respect to the farmer being highly creditworthy.

Liquidity is the ability of the farm business to meet fixed financial obligations (Turvey and Brown, 1990). One measure of liquidity FFSC recommends is working capital, which has been used in previous research (Splett, Barry, Dixon, and Ellinger, 1994). Thus, working capital to gross farm return, which relates the amount of working

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[4] Since a higher cut-off point represents more risk-averse farmers and is a conservative approach for lenders, alternative cut-off points of 1.05 and 1.50 are used to check for robustness.

capital to the size of the operation, is used as the independent variable to represent liquidity. The higher the ratio, the more liquidity the farm operation has to meet current obligations and the more creditworthy the farmer is.

FFSC defines solvency as the ability of the firm to repay all financial obligations by selling all assets. As a measurement of solvency, this paper uses the FFSC recommended debt-to-asset ratio. This ratio compares total farm debt obligations owed to the value of total farm assets and is one method of expressing the risk exposure of the farm business. As the debt-to-asset ratio increases, profitability and repayment capacity decrease, resulting in higher credit risk.[5]

Profitability is defined as the efficiency of the farm's activities and its ability to generate profit (Turvey and Brown, 1990). The FFSC recommended return on farm assets is commonly used to measure profitability (Turvey and Brown, 1990). The return on farm assets ratio measures the pretax rate of return on farm assets and can be used to measure the effective utilization of assets on business profitability. As this ratio increases, the utilization of assets is more effective so the farmer is more likely to be creditworthy.

FFSC defines financial efficiency as the measure of how well a business uses its assets to generate gross revenue and the effectiveness of production, purchasing, and financing decisions. The asset turnover ratio, which is the FFSC recommended measure of financial efficiency, quantifies the farm's efficiency of asset utilization. As the ratio increases, the farm becomes more efficient in the use of assets to generate revenue. Therefore, the farmer is more likely to be creditworthy.

In addition to liquidity, solvency, profitability, and financial efficiency, tenure is also included as an explanatory variable. Following Barry and Robison (1986), high

[5]Obviously a higher credit risk implies decreased creditworthiness.

tenure is typically associated with 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 gain on farmland. Thus, as tenure increases, the farm operator becomes more financially constrained, has lower repayment capacity and is less likely to be creditworthy.[6]

IV. Data Source and Data

Following Novak and LaDue (1994), Novak and LaDue (1997) and Zech and Pederson (2003), this study uses farm-level data to measure creditworthiness instead of the conventional practice of using lender data. The data come from the Illinois Farm Business Farm Management (FBFM) Association, which meets the following data certifications: FMV Balance Sheet certification and Family Living/Sources and Uses certification.[7] While lender data are preferred in credit scoring models, farm business records are used because lender data are difficult to acquire. Furthermore, unlike lender data, farm-level information gives the opportunity to develop credit scoring models with both low and high credit risk farmers (Escalante, Barry, Park and Demir, 2004). Another reason to use farm-level data instead of lender data is that this approach has been successfully used in previous research (Katchova and Barry, 2005; Escalante, Barry, Park, and Demir, 2004; Phillips and Katchova, 2004; Barry, Escalante, and Ellinger, 2002).

In FBFM data, there exist numerous alternatives for categorizing farmers. For instance, Plumley and Hornbaker (1991) use the net-farm-income-per-tillable-acre

[6] Therefore, the expected sign of the tenure variable coefficient is negative.
[7] These certifications are used because these certified data are the most reliable data.

variable (in the FBFM dataset) to determine whether a given farm is financially successful or less successful.

This research uses a sample of 8,212 farmer-years from 1995 to 2004.[8] Among these farmer-years, there are 2,272 unique farmers. By using farmer-years instead of ordinary years, the data are treated as a series of repeated cross sections. The repeated cross section data means each observation of the same farmer, provided it is recorded in a different year, is considered as a separate farmer-year (Lyons, 2006; Fay, Hurst, and White, 2002). This treatment of the data does not result in biased estimates or inflated test statistics (Allison, 1995).

The hog data from FBFM includes only family farms that also produce grain to feed their livestock. Hogs that are produced in factories instead of farms are not considered, since that requires private data. Although hog farms can also produce grain to feed their animals, hog and grain farms still differ from each other because they have different levels of leverage, equity, acreage, etc. Hence, this study considers hog farms and grain farms as different farm types.

The means and standard deviations for the farmer characteristics are reported in table 2 for each farm type from 1996-2004. For each variable, the first row refers to the mean, while the second row value (in parentheses and italics) refers to the standard deviation. Grain farms have very high mean values for the coverage ratio in 1997 and 2002, with high standard errors, while hog farms have large mean values in 2000 and 2004. For dairy farms, the greatest mean value for the coverage ratio occurs in 2004. In

[8] Note that each farmer does not necessarily exist for every year in the range. In other words, farmer 1 may exist in 1995 but not in 2000. Similarly, farmer 2 might exist in 2002 but not 2004. Also, since FBFM changed its data format beginning 1995, this study considers the range 1995 to 2004 and ignores observations before 1995.

addition, the average value of the coverage ratio is relatively unstable from 2001 until 2003 for grain farms compared to hog, dairy and beef farms. For grain, hog, dairy and beef farms, over the observed years, the average working capital to gross farm return, debt-to-asset, return on farm assets, asset turnover and tenure ratios are stable with low standard errors. For hog farms, the greatest mean value for working capital to gross farm return is 0.47 in 1996 and the lowest value is 0.03 in 1998. The greatest average asset turnover ratio value, 0.46, occurs in 2004. By contrast, the lowest value of 0.08 occurs in 2003. The mean value for the coverage ratio is negative in 1998 for hog and beef farms due to the fact that in those years cash inflows are negative, implying they incur losses during that year. In 1998 and 2002, the average values of return on farm assets are negative for hog farms. By comparison, beef farms exhibit a negative mean value for return on farm assets in only 1998.

As table 2 indicates, the mean values of most of the explanatory variables are different for grain and hog farms in 1998. Similarly, the average values for the tenure ratio is markedly different for grain and hog farms. Furthermore, grain farms differ from hog farms in mean values of working capital to gross farm return in 2004, debt-to-asset ratio in 2000, and asset turnover ratio in 2002 and 2003. Dairy and beef farms differ from grain and hog farms in average values for working capital to gross farm return and tenure ratio. In addition, the mean value of the tenure ratio for dairy and beef farms change over the years. Dairy farms differ from other farm types in mean value of asset turnover ratio in 2003.

In summary, table 2 shows that there are differences in farmer characteristics across farm types. Therefore, further analysis is necessary to examine whether separate regional credit scoring models should be developed for each farm type.

V. Results

Table 3 reports the marginal effects and standard errors for the logit model. The columns labeled "cut-off point 1" displays results for the case where the farmer is highly (less) creditworthy based on whether the coverage ratio is greater (less) than 1.[9] In the table, the marginal effects are calculated at the means of the explanatory variables. The interaction of the farm type dummy variables with explanatory variables explains for each farm type the effect each farm characteristic has on the probability that the farmer is highly creditworthy.

Table 3 shows the percent concordant and discordant.[10] The logit model correctly predicts the probability that a farmer is highly creditworthy 84.9% of the time. Table 3

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[9] Other than two categories, five risk classes are also created based on farmers' coverage ratios. Producers falling in the lower quartile (0% to 25% range) are assigned as class 5, representing the highest risk class; those in the 25% to 50% range are assigned as class 4; farmers in the 50% to 75% quartile are assigned as class 3; those falling in the 75% to 95% range are assigned as class 2; and farmers in the 95% to 100%(max) range are assigned as class 1, representing the lowest risk class because as the coverage ratio increases, the producer's creditworthiness increases. This type of classification creates a reasonable amount of data in each class. Moreover, this method fits with the Basel recommendation that there should not be more than 30% of loans in one class (Featherstone, Roessler and Barry, 2006).
When an ordered logit model is applied for five risk classes, the results show that the previous year's working capital to GFR, debt-to-asset, return on farm assets and tenure ratios are important for determining the creditworthiness of a farmer in the following year. The interaction of hog farms with the asset turnover ratio is significant, implying that hog farms differ from grain farms in their asset turnover ratios. The significance of the interaction of dairy farms with working capital to GFR implies that dairy farms differ from grain farms with respect to this financial measure.
[10] Concordant is the percent correctly predicted and discordant is the percent not correctly predicted.

also shows a p-value of zero for the null hypothesis that all coefficients in the model are zero. Therefore, the null hypothesis is rejected and the model is concluded to be valid.[11]

The results show that the previous year's working capital to GFR, debt-to-asset and return on farm assets ratios are important for determining the creditworthiness of a farmer in the following year and are consistent with the expected signs.[12] For instance, given that the explanatory variables are evaluated at their mean values, for a one unit change in working capital to GFR, the probability of a farmer being highly creditworthy increases by 0.04 units.

Considering the model as a whole, the fact that the beef farm dummy is significant and positive implies that the probability of a beef farmer being highly creditworthy is 0.94 units greater compared to a grain farmer. Since the dummies for years 1997 through 2002 are all significant and negative, compared to the base year 2004, the probability of a farmer being highly creditworthy is much less for these years.

Note that some of the interaction of farm type dummy variables with explanatory variables is significant, while some are not significant. For example, the interaction of hog farm type with working capital to GFR is not significant but the interaction of hog farm type with the debt-to-asset ratio is significant. This significance means the debt-to-asset variable has a different effect on creditworthiness for hog farms compared to grain farms. By contrast, the working capital to GFR variable is not significant. This insignificance means that the working capital to GFR variable has the same effect on

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[11] When testing whether all parameters except the base grain model are equal to zero (d1=d2=d3=0), the null hypothesis is not rejected (Prob > chi2 = 0.8047). In addition, the null hypothesis that parameters for specific farm types are equal to zero one at a time is not rejected ("test d1=0" Prob > chi2 = 0.9590; "test d2=0" Prob>chi2= 0.7044; "test d3=0" Prob>chi2= 0.3598). In conclusion, the general model is valid, but individual coefficients might be insignificant.

[12] GFR: Gross farm return. Note that the dependent variable is "highly creditworthy," not "creditworthiness."

creditworthiness for hog farms and grain farms. Debt-to-asset, return on farm assets, and asset turnover ratios have different effect on creditworthiness for hog farms compared to grain farms. However, working capital to GFR, the debt-to-asset, return on farm assets, asset turnover, and tenure ratios have the same effect on creditworthiness for dairy, beef, and grain farms.

These results show that the effect of farmer characteristics on creditworthiness differs across beef, hog and grain farms. Thus, separate credit scoring models are needed to account for these differences. Such models increase the efficiency of the credit scoring tools. Furthermore, with increased efficiency, lenders can more effectively differentiate between nonperforming loans and performing loans, thereby resulting in increased expected profit for the lender, better capital management, less bankruptcy, and less burden on the government and tax payers.

To ensure consistent results, alternative cut-off points, 1.05 and 1.50 (Zech and Pederson, 2003), are created and the model is re-estimated using these new cut-off points. The alternative model with 1.05 as the cut-off point shows that the previous year's working capital to GFR, debt-to-asset ratio, and return on farm assets are still significant in determining farmer creditworthiness. The 1997-2002 time dummies remain significant as well.[13] The beef farm dummy also remains significant. Hog farms consistently differ from grain farms in the effect the debt-to-asset and asset turnover ratios have on the probability of the farmer to be highly creditworthy, but return on farm assets for hog farms is not significant. When cut-off point 1.50 is used, only beef dummy variable

[13] Note that results are unchanged when outlier analysis is performed. In other words, despite executing the model after replacing the data that is outside of three standard deviations of the mean, with the mean plus/minus three standard deviations, the results remain unchanged.

becomes significant implying that the results are sensitive to which cut-off point is employed.

VI. Summary

This paper uses 1995-2004 FBFM data to examine farmer characteristics likely to be important in developing regional credit scoring models (credit scoring models specific to Illinois) that account for differences in farm type (hog, dairy, beef and grain). The coverage ratio, which is a FFSC recommended measure for repayment ability, is used as the dependent variable. Farmers are segmented into two categories: highly creditworthy and less creditworthy. The following explanatory variables are explored: working capital to gross farm return is used to measure liquidity; the debt-to-asset ratio is used to measure solvency; return on farm assets is used to measure profitability; the asset turnover ratio is used to measure financial efficiency; and owned acres as a percentage of total acres operated is used to measure tenure. The study employs a logit model, which is a common and widely accepted technique cited in previous literature (Turvey and Brown, 1990; Miller and LaDue, 1989; Zech and Pederson, 2003).

Results from the logit estimations indicate that the previous year's working capital to gross farm return, debt-to-asset ratio, and return on farm assets are the most pertinent factors for determining the creditworthiness of a farmer in the following year. The marginal effects for beef farms are larger than that for grain farms. Hog farms differ from grain farms in how the following financial characteristics impact farmer creditworthiness: solvency, profitability, and financial efficiency. Dairy and beef farms do not differ significantly from grain farms in the effect farmer characteristics have on the probability of a producer being highly creditworthy. Since the dummies for 1997 through 2002 are all significant and negative, compared to base year 2004, the probability of a farmer being highly creditworthy is significantly less for these years.

These results show that separate credit scoring models are needed for beef, hog and grain farms. Separate models are an improvement on existing credit scoring models as they more accurately assess farmer creditworthiness. Furthermore, with improved credit scoring methods, lenders can more effectively differentiate between nonperforming loans and performing loans, resulting in increased expected profit for the lender, better capital management, less bankruptcy, and less burden on the government and tax payers.

One weakness of this study is the loss of data by creating subcategories. Future research can gather more data so that the subcategories in the dataset can be expanded to have more observations. With an expanded dataset, supplemental research can take averages for the explanatory variables and reduce the volatility of income. A larger data set will ultimately yield more consistent results.

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Table 1: Variable Definitions and Expected Signs

Category	Variable	Definitions	Expected sign in regards to highly creditworthy farmer
Dependent Variable			
Repayment Capacity	Coverage Ratio	(Net Farm Income from Operations + Non-Farm Income + Depreciation + Interest on Term Debt + Interest on Capital – Income Taxes – Family Living Withdrawals) / (Annual Scheduled Principal + Interest Payments on Term Debt and Capital Leases)	
Independent Variable			
Liquidity	Working Capital to Gross Farm Returns	(Current Assets - Current Liabilities) / Value of Farm Production [a]	(+)
Solvency	Debt-to-asset Ratio	Total debt / Total Assets (fair market value)	(-)
Profitability	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	Asset Turnover Ratio	Value of Farm Production / Total Average Farm Assets (fair market value)	(+)
Tenure	Tenure	Owned Acres / Total Acres Operated	(-)

[a] Value of Farm Production= Crop Returns + Livestock Return above Feed + Custom Work + Other Farm Receipts

Table 2: Descriptive statistics

Variables	1996	1997	1998	1999	2000	2001	2002	2003	2004
GRAIN FARMS									
Observation number	265	332	372	391	506	519	557	559	618
Coverage ratio	1.30	16.11	0.32	0.46	0.66	1.26	12.37	1.24	1.84
	(6.51)	*(188.71)*	*(2.03)*	*(1.92)*	*(1.58)*	*(17.44)*	*(276.15)*	*(11.15)*	*(24.95)*
Working capital to gross farm return	0.41	0.39	0.37	0.33	0.36	0.33	0.28	0.30	0.33
	(0.54)	*(0.51)*	*(0.66)*	*(0.60)*	*(0.58)*	*(0.69)*	*(0.65)*	*(0.53)*	*(0.49)*
Debt-to-asset ratio	0.34	0.34	0.35	0.35	0.33	0.35	0.36	0.36	0.34
	(0.19)	*(0.18)*	*(0.19)*	*(0.20)*	*(0.19)*	*(0.20)*	*(0.20)*	*(0.20)*	*(0.19)*
Return on farm assets	0.12	0.07	0.01	0.04	0.05	0.02	0.02	0.06	0.08
	(0.08)	*(0.06)*	*(0.05)*	*(0.06)*	*(0.06)*	*(0.05)*	*(0.05)*	*(0.06)*	*(0.07)*
Asset turnover ratio	0.39	0.37	0.31	0.35	0.35	0.34	0.35	0.22	0.41
	(0.22)	*(0.18)*	*(0.16)*	*(0.21)*	*(0.20)*	*(0.20)*	*(0.22)*	*(0.42)*	*(0.24)*
Tenure ratio	0.22	0.21	0.22	0.22	0.24	0.24	0.24	0.23	0.22
	(0.22)	*(0.22)*	*(0.23)*	*(0.24)*	*(0.26)*	*(0.26)*	*(0.25)*	*(0.26)*	*(0.25)*
HOG FARMS									
Observation number	36	40	34	35	25	33	35	26	29
Coverage ratio	1.03	0.36	-0.29	0.85	41.12	0.48	0.20	1.27	5.66
	(1.98)	*(0.99)*	*(0.68)*	*(2.26)*	*(202.36)*	*(0.66)*	*(1.08)*	*(2.55)*	*(23.44)*
Working capital to gross farm return	0.47	0.42	0.03	0.35	0.38	0.40	0.22	0.34	0.45
	(0.56)	*(0.65)*	*(0.67)*	*(0.45)*	*(0.46)*	*(0.47)*	*(0.58)*	*(0.61)*	*(0.38)*
Debt-to-asset ratio	0.37	0.36	0.45	0.39	0.43	0.38	0.38	0.40	0.35
	(0.24)	*(0.20)*	*(0.22)*	*(0.22)*	*(0.21)*	*(0.21)*	*(0.19)*	*(0.23)*	*(0.19)*
Return on farm assets	0.12	0.05	-0.07	0.05	0.08	0.04	-0.03	0.02	0.14
	(0.06)	*(0.04)*	*(0.06)*	*(0.04)*	*(0.05)*	*(0.04)*	*(0.06)*	*(0.10)*	*(0.07)*
Asset turnover ratio	0.36	0.31	0.24	0.31	0.39	0.32	0.24	0.08	0.46
	(0.16)	*(0.10)*	*(0.14)*	*(0.13)*	*(0.18)*	*(0.16)*	*(0.09)*	*(0.27)*	*(0.24)*
Tenure ratio	0.30	0.30	0.26	0.32	0.28	0.38	0.33	0.40	0.33
	(0.25)	*(0.27)*	*(0.25)*	*(0.30)*	*(0.32)*	*(0.28)*	*(0.28)*	*(0.31)*	*(0.28)*

Table 2: Descriptive statistics continued

Variables	1996	1997	1998	1999	2000	2001	2002	2003	2004
DAIRY FARMS									
Observation number	4	5	4	7	9	11	11	6	8
Coverage ratio	0.55	0.71	1.10	0.72	0.50	0.97	0.64	0.50	305.46
	(0.38)	*(0.58)*	*(0.91)*	*(1.09)*	*(0.41)*	*(0.97)*	*(0.55)*	*(0.44)*	*(861.90)*
Working capital to gross farm return	0.03	0.18	0.26	0.10	0.04	0.06	0.00	0.12	0.39
	(0.59)	*(0.35)*	*(0.14)*	*(0.20)*	*(0.21)*	*(0.19)*	*(0.18)*	*(0.17)*	*(0.55)*
Debt-to-asset ratio	0.44	0.40	0.29	0.27	0.31	0.26	0.37	0.36	0.33
	(0.10)	*(0.23)*	*(0.19)*	*(0.19)*	*(0.21)*	*(0.19)*	*(0.17)*	*(0.20)*	*(0.19)*
Return on farm assets	0.10	0.02	0.10	0.05	0.04	0.05	0.04	0.08	0.10
	(0.07)	*(0.07)*	*(0.04)*	*(0.10)*	*(0.04)*	*(0.07)*	*(0.03)*	*(0.05)*	*(0.04)*
Asset turnover ratio	0.41	0.43	0.40	0.40	0.31	0.38	0.38	0.00	0.33
	(0.13)	*(0.11)*	*(0.16)*	*(0.13)*	*(0.12)*	*(0.15)*	*(0.12)*	*(0.00)*	*(0.09)*
Tenure ratio	0.41	0.27	0.38	0.46	0.62	0.42	0.51	0.55	0.70
	(0.33)	*(0.24)*	*(0.22)*	*(0.35)*	*(0.35)*	*(0.36)*	*(0.37)*	*(0.38)*	*(0.32)*
BEEF FARMS									
Observation number	7	3	2	4	5	5	6	6	8
Coverage ratio	0.09	0.23	-0.02	0.84	0.16	0.13	0.12	0.50	0.24
	(0.41)	*(0.25)*	*(0.10)*	*(1.37)*	*(0.16)*	*(0.14)*	*(0.11)*	*(0.33)*	*(0.30)*
Working capital to gross farm return	0.52	0.03	0.54	0.27	0.69	0.40	0.81	0.80	0.65
	(0.58)	*(0.59)*	*(0.24)*	*(1.29)*	*(0.53)*	*(0.15)*	*(0.53)*	*(0.64)*	*(0.61)*
Debt-to-asset ratio	0.45	0.34	0.26	0.26	0.39	0.42	0.35	0.32	0.35
	(0.17)	*(0.17)*	*(0.03)*	*(0.19)*	*(0.16)*	*(0.12)*	*(0.19)*	*(0.17)*	*(0.20)*
Return on farm assets	0.08	0.02	-0.01	0.04	0.01	0.01	0.02	0.17	0.06
	(0.03)	*(0.04)*	*(0.04)*	*(0.08)*	*(0.05)*	*(0.04)*	*(0.05)*	*(0.10)*	*(0.06)*
Asset turnover ratio	0.37	0.26	0.15	0.21	0.27	0.27	0.23	0.34	0.32
	(0.24)	*(0.23)*	*(0.10)*	*(0.19)*	*(0.09)*	*(0.09)*	*(0.11)*	*(0.51)*	*(0.13)*
Tenure ratio	0.39	0.45	0.57	0.33	0.19	0.26	0.16	0.18	0.21
	(0.43)	*(0.41)*	*(0.33)*	*(0.41)*	*(0.18)*	*(0.16)*	*(0.13)*	*(0.14)*	*(0.15)*

The numbers in italics are standard deviations.

Table 3: Logit Results

Explanatory Variables	Cut-off point 1 [a] Marginal Effect	Standard Error
Lagged Working Capital to GFR	0.04	(0.01)***
Lagged Debt-to-asset	-0.41	(0.03)***
Lagged Return on Farm Assets	0.17	(0.06)***
Lagged Asset Turnover	0.03	(0.02)
Lagged Tenure	0.02	(0.01)
Dummy-Hog Farm	0.00	(0.05)
Dummy-Dairy Farm	-0.02	(0.05)
Dummy-Beef Farm	0.94	(0.05)***
Dummy-1996	-0.01	(0.01)
Dummy-1997	-0.03	(0.01)***
Dummy-1998	-0.06	(0.01)***
Dummy-1999	-0.03	(0.01)***
Dummy-2000	-0.02	(0.01)*
Dummy-2001	-0.04	(0.01)***
Dummy-2002	-0.04	(0.01)***
Dummy-2003	-0.01	(0.01)
Hog-Working Capital to GFR	0.01	(0.03)
Hog-Debt-to-asset	0.19	(0.08)**
Hog-Return on Farm Assets	0.36	(0.19)*
Hog-Asset Turnover	-0.24	(0.09)**
Hog-Tenure	0.07	(0.04)
Dairy-Working Capital to GFR	-0.04	(0.08)
Dairy-Debt-to-asset	0.16	(0.13)
Dairy-Return on Farm Assets	0.18	(0.36)
Dairy-Asset Turnover	0.11	(0.12)
Dairy-Tenure	0.03	(0.07)
Beef-Working Capital to GFR	-0.37	(0.29)
Beef-Debt-to-asset	-0.64	(0.87)
Beef-Return on Farm Assets	-1.32	(1.16)
Beef-Asset Turnover	-0.01	(0.48)
Beef-Tenure	-0.37	(0.43)
Log likelihood	-1339.9905	
Number of observations read	8212	
Number of observations used	4523	
LR chi2(31)	920.25	
Prob > chi2	0.0000	
Pseudo R2	0.2556	
Percent Concordant	84.9	
Percent Discordant	14.8	
Percent Tied	0.3	

[a] The "cut-off point 1" represents the case where coverage ratio>=1,

that is farmer is highly creditworthy, otherwise less creditworthy.

Note: Marginal effect is for the logit model. Standard errors for the marginal effects are in parentheses. *** represents p-value<=0.01, ** represents p-value<=0.05, and * represents p-value<=0.10.