Selected Paper prepared for presentation at the American Agricultural Economics Association Annual Meeting, Long Beach, California, July 23-26, 2006

Credit Risk and Financial Performance Assessment of Illinois Farmers:

A Comparison of Approaches with Farm Accounting Data

Tianwei Zhang

Paul N. Ellinger

May 2006

Contact Information:

Tianwei Zhang
University of Illinois at Urbana-Champaign
326 Mumford Hall, MC-710
1301 West Gregory Drive
Urbana, IL 61801
Tel: (217) 333-2616
Fax: (217) 333-5538
E-mail: tzhang2@uiuc.edu

 Tianwei Zhang is Ph.D. student and Paul N. Ellinger is an associate professor in the Department of Agricultural and Consumer Economics at the University of Illinois at Urbana-Champaign.

Abstract

Pro forma financial performance evaluation of agricultural producers is an important issue for lenders, internal management and policy makers. Lenders strive to improve their credit risk management. Internal management is interested in understanding the financial impacts of alternative strategic decisions. And policy makers often assess the magnitude and distributional effects of alternative policies on the future financial performance of farm business.

Data limitations are a major impediment in assessing farm financial performance. Most traditional farm operations are private firms and thus, public traded equity information which can be converted into market valuation change is not available. Moreover, historical loan performance data on agricultural loans such as past due and defaults are not readily available. These aspects present substantial methodological issues when establishing an independent variable to use in assessing future performance.

Credit risk modeling and financial performance assessment have been remotivated and gained unprecedented academic attention in recent years(Barry 2001, Kachova and Barry 2005, Saunders and Allen 2002). However, some of the new approaches and models have limitations when applied to agricultural producers. Adapting the models and approaches to utilize the available information of farm business needs careful attention and validation.

In this paper, Altman's $Z^{'}$ score model and $Z^{''}$ score model are applied to farm accounting data for the detection of farm operating and financial difficulties. i.e., farms with high credit risk. The well-developed and widely used Altman models have not been

applied to agricultural data. The results are compared to an experienced based credit risk migration model (Splett, et al) and a logistic, lender-based model (Featherstone, Roessler, and Barry 2006). The experience based model is a primary model used in the current farm credit analysis. The logistic model is claimed for better statistical prediction accuracy and no binding assumption on multivariate normality (Altman 1968). Results from each of these models are compared across a common database of Midwestern grain farms.

Farms are grouped into different categories with different levels of financial. Instead of focusing on farm loan defaults, earned net worth growth rate (ENWGR) and term debt coverage ratio (TDCR) are used as two major indicators for financial stress situation of farm credit quality.

1. Introduction

Credit risk is the risk of default or of market value deterioration caused by the change of the obligator's credit quality. Default is a special case of credit quality downgrade when the credit quality deteriorates to the point where the obligator cannot meet its debt obligation. The borrower is either unable or unwilling to fulfill the terms promised under the loan contract. Farm credit risk is the uncertainty of paying the agricultural loan in full in a timely way. Credit risk is a primary source of risk to financial institutions, and the holdings of capital including loan loss allowances and equity assets are main responses to such risk (Barry, 2001).

Credit risk evaluation in agricultural loans is important to farmers, agricultural lenders, and policy makers. More accurate credit risk evaluation leads to more precise loan pricing, lower loss rates, and reduced capital management costs. Agricultural lenders may benefit directly from making farm loan decisions efficiently and consistently through objective, numerically-based credit risk evaluation. With improved credit risk models, lenders can monitor loan portfolio loss exposure, make appropriate reserve policies, and meet safety and soundness regulation requirements. Also, the contingent costs from regulations, government loan programs, and taxpayers who ultimately bear the costs of risk bearing are less.

When agricultural lenders make loan decisions, they have asymmetric information about their borrowers and they cannot get external sources such as rating agencies data or publicly traded company stock data[1]. Access and availability to high-quality, historical loan data for agricultural borrowers has been a primary issue in estimating and evaluating credit risk and financial performance models. In general, the two approaches have been to

[1] Third party ratings such as S&P rating or KMV rating.

use lender data or farm accounting data (Miller and LaDue 1989). The selection of the dependent variable, usually defaulted loans or problematic borrowers, for lender data models is usually constructed from real data. Statistically-based credit scoring models, such as linear probability model, discriminant analysis model, Logit model and Probit model can be applied to determine the factors that contribute to credit risk (Turvey, 1991). However statistically-based models do not always give better prediction of credit risk and defaults than experience-based models (Splett, Barry, Dixon and Ellinger, 1994).

Loan data are biased on the aspect that lenders only keep records on the accepted loans, but not the rejected applications which are often the problematic borrowers. Studies utilizing farm accounting data do not suffer from this bias and are generated from more random sampling since they do not discard problematic borrowers. But, they can be exposed to survival bias due to the voluntary nature of the membership in state-record keeping associations. Moreover, the definition of the independent variable used in these models is also problematic. Often thresholds of specific financial ratios are used to measure performance.

An issue not addressed in previous studies is the ability of credit evaluation models to evaluate performance across alternative data. Statistical performance is often represented within the estimation sample or data, but there is little evidence regarding the generalization of the models to alternative data. Accounting data for a 5 year panel of farms are used to evaluate and compare measures of credit risk and financial performance across models developed with a different data set

To address this lack of lender-side data, credit risk migration analysis (Barry, Escalante and Ellinger, 2002) and option pricing approaches (Katchova and Barry, 2005) have been utilized to estimate farmers' credit risk. The migration approach is an extension of traditional financial ratio analysis and has several applications in farm credit risk analysis (Barry, Escalante and Ellinger, 2002). Since the classification cutoff values are based on experience, this approach still has the characteristics of experience based models.

The option pricing approaches also need to be applied with caution. First, the strength of option pricing approach is to transform equity market value into assets market value through Black-Scholes-Merton option pricing formula (Black and Scholes, 1973; Merton, 1974). Since farms are private firms, publicly traded and observable equity data are unavailable. Therefore, the mean and variance of farm assets values estimated using accounting data are not the required market value in the option pricing model for credit risk analysis.

Katchova and Barry applied the approach using farm accounting data, but only required a minimum of two annual data points to characterize the distribution and estimate the variance. This method is not likely robust nor comparable to using daily stock price information to characterize the asset distribution as other corporate finance studies have done. Second, in the applied option pricing models, such as Creditmetrics and KMV,[2] the actual defaults are collected. Therefore, the model outputs can be mapped into long time series and large cross sectional database with the actual defaults to generate the proper credit score. Without extensive historical data and cross sectional defaults, the option pricing model may not be statistically sound.

The overall objective of the paper is to evaluate and compare well-accepted models applied in corporate finance: the Z score models (Altman), with major models

[2] CreditMetrics and KMV are the applied credit risk models developed by J.P. Morgan and Moody's.

applied in agricultural finance: the experience-based credit scoring model (EBCSM) and the logistic model employed by Featherstone, Roessler, and Barry (FRB). If the farm stress can be modeled and predicted with farmer side accounting data, then the likelihood of being default is signaled to borrowers, lenders and relative policy makers. The Z score models and FRB's model were developed with the aid of lender data. EBSCM used an experience based model to assess performance. Specific objectives of this paper are:

1. to apply a well-defined and well-accepted credit risk model in corporate finance—Altman's Z score models to farm performance and credit risk analysis.
2. to compare the classifications, ranks and correlations of alternative credit scoring models using a common database, and
3. to investigate the relationship between credit score and future financial performance and stress.

In the following sections, the previous farm credit risk studies are reviewed and Altman's Z score models and the farm credit models are summarized. By developing Altman's Z score models and agricultural credit models with farm accounting data, the stress indicators are tested by assessing the statistical characteristics and changing trends among different risk groups. The models are compared and used to predict farm financial stress.

2. Literature Review

In generally terms, credit risk measurement approaches can be classified into three categories. The first categories are the "expertise" or "experience" models, for example the 5C's approach.[3] They are judgmental-based analysis with lender's experience and borrower's repayment history. This kind of approaches is time and labor intensive and often ratio somewhat arbitrary thresholds are established. The subjective assessment may not be statistically correlated to risk. However, the approach it is the most commonly used at commercial banks (Ellinger, Splett and Barry).

The second general category is statistically-based methods including the linear model, the Logit model, the Probit model and the discriminant analysis model. These models estimate either a credit risk score or a probability of default for distinguishing borrowers (Sanders and Allen, 2002). Usually lender-side loan data are used. Among all statistically-based models, Altman's Z score models were one of the fist to be developed and are still being used by lenders and practitioners. The criticism of statistical models includes the lacking of theoretical backup, linearity and distribution assumptions, and the ability of models to generalize to data not in the estimation sample.

In the third general category, more recent approaches have been developed by using mark-to-market data. The option pricing theory developed by Black, Scholes and Merton is the core of this type of models (Blank and Scholes, 1973; Merton, 1974). Since the market value fluctuation of borrower's assets is the fundamental source of credit risk and the fast moving changes in borrower's conditions cannot be captured by accounting data, the observable information from the stock market is a reliable evidence to predict borrower's credit worthiness. The leading applications of the option pricing models are CreditMetrics© by J.P. Morgan and KMV© by Moody's. A good review of CreditMetrics and KMV models can be drawn from Crouhy, Galai and Mark (2000).

[3] 5 "Cs" of credit risk evaluation: Character (reputation), Capital (leverage), Capacity (volatility of earnings), Collateral (repayment guarantee), and Conditions of the borrowers.

Consistency of credit evaluation at agricultural banks was examined by Ellinger, Splett, and Barry (1992) with survey data from 717 agricultural banks. Their results showed large degree of dispersion in the use, implementation and design of lender credit scoring models. It indicated the lack of efficient data and uniform model for lenders to evaluate the creditworthiness of agricultural borrowers. The models compared in this study were primarily experience based models.

Turvey (1991) compared four statistically based models: linear probability, discriminant method, Logit and Probit models using farm loan observations in Canada. The results show that the model predictive accuracies do not have significant differences among the four approaches. Ziari, Leatham and Turvey (1995) used actual loan data to evaluate the risk classification performance of parametric statistical models with nonparametric models. They concluded that two types of models only differ slightly in the classifying accuracy.

This study utilizes and compares the Altman's Z score models, EBSCM and FRB using a five-year farmer panel. The Altman model was first proposed by Altman in 1968 and then extended in 1977 and 2004 (Altman, 1968; 1977; 2004). One of the extended model, known as ZETA model[4] is widely applied by finance business practitioners. The model is also extended to firms not traded publicly and to the non-manufacturing firms. The model specifications are described in the following section.

3. Model Specification

[4] ZETA model uses more variables than the original Z score model. Altman et. al. claimed that ZETA model predicts more accurate for longer time periods. But ZETA is a proprietary model and the parameters are not publicly available.

This study compares four models. Since the original Altman's Z score model is applicable to publicly traded entities and requires stock market data, this study utilizes two extended models: Altman's $Z^{'}$ score model developed for private firm and Altman's $Z^{''}$ score model developed for non-manufacture type private firms (Altman, 2004). The experience based model EBSCM and the statistically based FRB model are the third and fourth models used to rank, classify and compare farms.

3.1 Altman's $Z^{'}$ Score model and $Z^{''}$ Score Model

Altman's $Z^{'}$ score model uses five dependent variables out of the original 22 after sample selection and variable selection.

$$Z' = 0.717X_1 + 0.847X_2 + 3.107X_3 + 0.42X_4 + 0.998X_5 \quad (1)$$

X_1= working capital / total assets,

X_2= retained earnings / total assets,

X_3= earnings before interest and taxes / total assets,

X_4= total equity / total liabilities,

X_5= sales / total assets, and

$Z^{'}$ = overall index

X_1 is a measure of the net liquid assets of farm relative to the total capitalization. Working capital is the difference between current assets and current liabilities. This financial ratio considers the liquidity and size characteristics explicitly. Usually a shrinking X_1 indicates consistent operating losses of farm. X_2 is a ratio that measures the cumulative profitability over time. This ratio reports the cumulative share of farm's net earnings net of family living withdrawals and income taxes reinvested for next year. A relatively young farmer probably shows lower X_2 than older farmers. X_3 and X_4 measures the farmer's profitability and solvency. X_5 the capital turnover ratio is a measure of the management's efficiency. It illustrates the sales generating capability of assets employed on the farm. With equation (1), a Z' score is computed for each farm in each year.

Altman's Z' score equation's weights and classification boundaries are generated from the discriminant analysis. This study adopts the same weights and boundaries to investigate the direct application of the significant statistical characteristics on the farm stress indicators. In the Altman's Z' score model the lower boundary is 1.23 and the upper boundary is 2.9. A below 1.23 Z' score indicates high credit risk and an above 2.9 Z' score indicates low credit risk. Therefore farms are grouped into three different credit risk classes.

Another extension Altman made on his original model is called Z'' score model (Altman, 2004). The difference between Z' and Z'' is the elimination of the last variable X_5— an industry-sensitive ratio in equation (1). The weights changed as well. The purpose of Z'' score model is to minimize the potential industry effect which is more likely to take place when X_5 is included. For the farm sample, the moments and distributional properties of this ratio X_5 vary the most from Altman's sample. For example, the average for successful borrowers in Altman's study is 1.9 whereas the average for the farm sample is 0.27. But eliminating the asset turnover ratio provokes the understanding of credit risk change without the influence of farm and business types.

$$Z'' = 6.56X_1 + 3.26X_2 + 6.72X_3 + 1.05X_4 \quad (2)$$

A below 1.1 Z'' score indicates high credit risk and an above 3.15 Z'' score indicates low credit risk. Farms are grouped into three risk classes with the computed Z'' scores.

3.2 Experience Based Credit Risk Model (EBCRM)

EBCRM is a credit scoring method developed by Splett et al. to classify farms. They used borower data provided by the Farm Credit Bank of St. Louis. Instead of using real loan repayment performance classification, loans are classified by the borrower's farm business performance. With an experience-based model, FFSC dependent variables[5], variables weights, and interval cutoff points were established and a credit score was computed for each loan. An important contribution of their study is the credit scoring method to classify the loans by farm performance measures, i.e., the FFSC financial measures. It initialized the credit risk evaluation from the borrower's side.

Five key measure variables are chosen by the farm lending expert panel.[6] They are liquidity, profitability, repayment capacity, and efficiency. For each variable, five interval ranges are defined (See Table 1). Each farm has five scores on liquidity, solvency, profitability, repayment capacity and financial efficiency accordingly. These five scores are weighted to generate a total score between 1 and 5. Then, each farm is grouped to a credit risk class.

$$\begin{aligned} score &= 10\%\ liquidity + 35\%\ solvency + 10\%\ profitability \\ &\quad + 35\%\ repayment\ capacity + 10\%\ financial\ efficiency \end{aligned} \tag{3}$$

Equation (3) provides the weights for the factors. Unlike Z' score and Z'' score, the weights are generated from experience. The 5 risk classes used in the original study are mapped into 3 categories for purposes of comparing the Altman models. Classes 1

[5] The measure variables are picked by utilizing FFSC (Farm Financial Standards Council)'s 16 financial measures. The five variables appeared in the model are picked under five categories: liquidity, solvency, profitability, repayment capacity, financial efficiency.
[6] The expertise values used in this approach are all developed by the Farm Credit Bank of St. Louis panel and University of Illinois researchers.

and 2 are mapped into the lowest risk class, classes 3 and 4 into moderate risk and class 5 is the high risk class.

3.3 Binary Logistic Model for Estimating the Probability of Default (FRB)

The most recent statistically based credit risk model is the logistic model estimating the probability of default of 157,853 loans within the Seventh Farm Credit District (Featherstone, Roessler and Barry). They utilized historical financial origination ratios based on underwriting standards to predict the probability of default of different loan types. The estimated probability of default is mapped into a similar default risk grid of S&P publicly rated firms for appropriate loan pricing. The results indicate that repayment capacity, owner equity and working capital are important determinants of probability of default.

The FRB model defines default as a payment being ninety days or more past due at least once since origination. This is the traditional and widely-applied definition for default. Two classes of default and not-default construct the binary dependent variable. Three origination ratios are used as the independent variables: Capital Debt Repayment Capacity Percentage (CDRC), Owner Equity Percentage (OE), and Working Capital Percentage (WC). The regression results for the overall model show that all three ratios are significant in the model.

$$\ln\left(\frac{probability\ of\ default}{1-probability\ of\ default}\right) = -2.3643\ CDRC - 0.00135\ OE - 0.0217\ WC \qquad (4)$$

With equation 4, the probability of default is estimated for each farm. FRB chose a cutoff value of 2% for classifying default. The proposed FCS guidelines reported in their study suggest a cutoff of between 0.26 and 0.52 for BBB- loans. The grouping of three classes for FRB are based on PD cutoffs of 0.50% and 2%.[7]

3.4 Stress Indicators

This study adopts the results from Zech and Pederson (2003) as the stress indicators. The first stress indicator is the Term Debt Coverage Ratio (TDCR). The second stress indicator is the Earned Net Worth Growth Rate (ENWGR). The Term Debt coverage ratio calculation is the standard established by FFSC. Earned net worth growth is calculated as:

NWGR =

$$\frac{\text{Net farm income + Net nonfarm income - withdrawals - income taxes}}{\text{Total equity capital at beginnning of year}}$$

Similar to Zech and Pederson, the stress indicators are calculated as averages. The averaging of the dependent variables removes some of the year-to-year volatility inherent in farm income and provides a slightly longer-term stress index.

4. Data

This study uses the annual farm data from 2000 through 2004 provided by the Illinois Farm Business and Farm Management (FBFM) Association. FBFM is an informative database with Illinois farmers' financial information. Cost and market values of assets and liabilities are available as well as farm and nonfarm income and expenditure data. There are 399 sole proprietors that meet the consistency and field staff validation

---

[7] There is no intent to attempt to make the three categories in each model represent a comparable amount of risk. The categorical representations provide one mechanism to compare the results across models and identify the observations that may result in inconsistent ranking.

criteria to be included in a comparative data set over the entire five year sample. Verification procedures included certifications on cost and market asset valuation; income certification; and farm and nonfarm cash flow expenditure validation.

Previous studies using the FBFM data typically only utilize a 2 year continuous sample (Kachova and Barry 2005, Phillips and Kachova 2005). A more consistent analysis result is expected since this study does not include the farms that drop out or enter in the database during a 5-year period. Moreover, the extended sample allows for the testing of model performance in years subsequent to initial credit evaluation and scoring.

Table 2 shows the univariate distributions of the two stress indicators and the descriptive statistics for the score variables for each year. The average ENWGR ranged from a low of -1% in 2001 to a high of 5% in 2004, while the average TDRC ranged from 2.74 in 2003 to 21.38 in 2001. The average Z score and the proportion of high risk borrowers for the Altman 1 model are substantially larger than the Z score for the Altman 2 model. This is primarily due to the inclusion of the capital turnover (sales to asset) ratio. Agricultural businesses tend to be more capital intensive and have higher proportions of assets relative to sales. For example, the average ratio for agricultural borrows in the sample is 0.27 whereas in the Altman original study the average was 1.9. Since the coefficient on this ratio is approximately 1.0, the result is a difference of over 1.5 in the calculated Z score and hence, a higher proportion of borrowers classified as high risk. Similar to FRB results, a substantial proportion of borrowers are grouped in the 2 to 2.5% range and thus, a higher proportion of borrowers are classified in the high risk FRB class.

6. Results

Comparisons of the classification results over the entire 5-year period are provided in Table 3. Values on the diagonals of each sub matrix indicate the risk categories are similar between the two models. Large inconsistencies occur with the Altman models. For example, 135 of the 813 borrowers classified as high risk for Altman 1 are classified as low risk in the Altman 2 model. Another major discrepancy occurs between the FRB model and Altman 2 model. Almost 10% of the borrowers classified as low risk in the Altman 2 model are classified as high risk in the FRB model.

The classification procedures are not standardized across the models. Another method to compare the models is to measure simple correlation coefficients of the raw scores of each model. The Spearman rank correlation coefficients for the models are provided in Table 4. The rank correlation among all the models is very strong ranging from -0.79 between EBSCM and Altman 2 to 0.966 between the two Altman models.[8] Indications are that the ranking of farms is similar across the models whereas the distribution and classifications of the models differ.

Effective risk rating models should have a strong relationship to future financial performance and be able to identify future financial stress. Two stress measures are calculated in each year – earned net worth growth (ENWGR) and term debt and capital replacement ratio (TDCR). To remove some of the year-to-year variability prevalent in farming, the measures are averaged over a two-year period. The results for credit score

[8] Negative correlations for the PD and EBCSM are a result of the reversal of the direction of high and low risk farms represented by the score. A low PD and EBCSM score are low risk whereas a low Z score is high risk.

classifications generated in 2000 for periods 2001-02, 2002-03, and 2003-04 are provided in Table 5. The mean values and significant differences of means across credit rating classes for each of the stress indicators are provided. In general, the directional effects are as expected. The low risk models result in stronger earnings and repayment performance in future periods. As expected the significance tends to decline as the prediction time frame lengthens.

Poor loan performance is often dictated by extremely stressed conditions. Another approach to assess and compare the models is to establish a stress threshold where the performance ratio is categorized as high risk (Zech and Pederson). For each of the two ratios, a cutoff threshold is used to separate high risk farms from other farms. The values for ENWGR and TDCR are 0.00 and 1.00 respectively. Credit scores are then used to evaluate the proportion of farms that exceed the threshold in future periods.

The mean results and statistical differences based on credit scores in 2000 are reported in Table 6. Each percentage value represents the proportion of the 399 farms that did not exceed the stress threshold in each respective period. For example, the 32.47% value for ENWGR for 2001-02 indicates that for all farms classified as low risk with the Altman 1 model in 2000, 32.47% of the farms will be below the stress threshold of 0 in 2001-02. Again, the general direction of each of the models is consistent with expectations. The EBCSM was the only model that exhibited statistical differences in each year for ENWGR.

A final comparison among the models involves estimating a simple logit model measuring the relationship between the raw credit score (or PD) and the high risk threshold classifications for each future period. Graphical results are provided in Figures

1 and 2. The steeper the curve, the stronger the relationship between the credit score and future financial performance and stress.

The agricultural models (EBCSM and FRB) tend to have stronger relationships with both the earnings and repayment stress indicators. The Altman models did not have a strong relationship with future repayment analysis. This is likely due to the inclusion of repayment capacity in the agricultural models and the linkage over time of repayment capacity.

7. Conclusion

This study applies the Altman's $Z^{'}$ (Altman 1) score and $Z^{''}$ (Altman 2) corporate finance scoring models to agricultural producers and compares the results to an experience based and statistically-based agricultural models. With the Illinois farm accounting data, farms are grouped into high, medium, and low credit risk levels under each model. The classification effects are tested and the results show that all models can classify farms into different risk levels. Two stress indicators are used to assess the relationships the models have with future performance.

In general the models were highly correlated and resulted in consistent ranks. However, the distribution of the scores and classification rules of the models differed. The models tended to be related to short-term future performance, but the relationship declined over time.

The Altman models do not perform as well and some inconsistencies occur in classification. This is likely due to the inherent differences of financial ratios between corporate borrowers and agricultural firms. An extension of this analysis would be to re-weight the discriminant function for agricultural purposes.

References

Altman, E., “Financial Ratios, Discriminant Analysis and the Prediction of Corporate Bankruptcy.” *Journal of Finance*, 23-4 (1968): 589-609.

Altman, E., R. Haldeman, and P. Narayanan, “ZETA Analysis: A New Model to Identify Bankruptcy Risk of Corporations.” *Journal of Banking and Finance*, 1-1 (1977): 29-54.

Altman, E., “Predicting Corporate Distress in a Turbulent Economic and Regulatory Environment.” *Rassegna Economica*, 68-2 (2004): 483-524.

Barry, P.J. “Modern Capital Management by Financial Institutions: Implications for Agricultural Lenders.” *Agricultural Finance Review*, 61 (2001): 103-122.

Barry, P.J., C.L. Escalante, and P.N. Ellinger. “Credit Risk Migration Analysis of Farm Businesses.” *Agricultural Finance Review*, 62(2002):1-11.

Black, F. and M. Scholes, “The Pricing of Options and Corporate Liabilities”, *Journal of Political Economy*, 81-3 (1973): 637-654.

Crouhy, M., D. Galai, and R. Mark. “A Comparative Analysis of Current Credit Risk Models.” *Journal of Banking and Finance*, 24(2000): 59-117.

Ellinger, P.N., N.S. Splett, and P. J. Barry. “Consistency of Credit Evaluations at Agricultural Banks.” *Agribusiness: An International Journal*, 8(1992): 517-536.

Giesecke, K. "Credit Risk Modeling and Valuation: An Introduction." *Final Draft* October, 2004.

Katchova, A.L. and P.J. Barry. "Credit Risk Models and Agricultural Lending." *American Journal of Agricultural Economics* 87(2005):194-205.

Levene, H. "Robust Tests for the Equality of Variance." in *Contributions to Probability and Statistics,* ed. I. Olkin, Palo Alto, CA (1960): Stanford University Press, 278 - 292.

Miller L.H. and LaDue E.L., "Credit Assessment Models for Farm borrowers: A logit Analysis", Agricultural Finance Review, Vol 49., 1989.

Merton, R., “On the Pricing of Corporate Debt: The Risk Structure of Interest Rates.” *Journal of Finance* 28(1974): 449-470.

Saunders, A., and L. Allen. Credit Risk Measurement: New Approaches to Value at Risk and Other Paradigms, 2nd ed. NewYork: John Wiley and Sons, 2002

Splett, N.S., P.J. Barry, B.L. Dixon and P.N. Ellinger. “A Joint Experience and Statistical Approach to Credit Scoring,” *Agricultural Finance Review* 54(1994): 39-54.

Turvey, C., “Credit Scoring for Agricultural Loans: A Review with Applications,” *Agricultural Finance Review*, 51(1991): 43-54.

Ziari, H.A., D.J. Leatham and C.G. Turvey. “Application of Mathematical Programming Techniques in Credit Scoring of Agricultural Loans,” *Agricultural Finance Review*, 55(1995).

Table 1. Credit scoring and classification intervals for EBCSM model

	Score				
	1	2	3	4	5
Variables (Measures)	Interval Range				
Liquidity (Current Ratio)	>2	1.6-2	1.25-1.6	1-1.25	<1
Solvency (Equity/Asset Ratio)	>0.8	0.7-0.8	0.6-0.7	0.5-0.6	<0.5
Profitability (Farm Return on Equity)	>0.1	0.06-0.1	0.04-0.06	0.01-0.04	<0.01
Repayment Capacity (Capital Debt-Repayment Margin Ratio)	>2.5	2.0-2.5	1.5-2.0	1.0-1.5	<1.0
Financial Efficiency (Net Farm Income from Operation Ratio)	>0.4	0.3-0.4	0.2-0.3	0.1-0.2	<0.1

Table 2. Descriptive statistics of stress indicators and score variables for each model

	2000		2001		2002		2003		2004	
Stress	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.
TDCR	8.15	48.82	21.38	256.67	3.91	21.24	2.74	5.51	6.37	39.77
ENWGR	0.02	0.05	-0.01	0.05	0.00	0.04	0.03	0.04	0.05	0.06
Altman 1 Score	2.09	2.79	2.09	3.47	1.81	2.36	2.01	2.87	2.33	3.12
Altman 2 Score	5.83	7.38	5.75	9.07	5.04	6.30	5.59	7.52	6.52	8.19
Score	3.12	1.12	3.52	1.07	3.45	1.07	3.07	1.10	2.76	1.08
PD	0.02	0.01	0.02	0.02	0.02	0.01	0.02	0.01	0.02	0.01

# of Farms	399			399			399			399			399		
Risk Level	L	M	H	L	M	H	L	M	H	L	M	H	L	M	H
Altman 1 Model	77	159	163	75	136	188	75	138	186	83	164	152	93	182	124
Altman 2 Model	261	105	33	244	108	47	234	120	45	276	92	31	299	83	17
EBCSM Model	164	187	48	119	198	82	121	216	62	173	192	34	214	167	18
FRB Model	69	189	141	56	174	169	58	175	166	64	196	139	72	216	111

L = low risk, M=Moderate risk and H = high risk

Table 3. Classification Matrix: Credit Classes, 1995 observations, 399 farms per year, 2000-04.

		Altman 1 Class			Altman 2 Class			FRB Category			EBCSM Class		
		Low risk	Mid risk	High risk	Low risk	Mid risk	High risk	Low risk	Mid risk	High risk	Low risk	Mid risk	High risk
Altman 1 Class	Low risk	x	x	x	403	0	0	263	137	3	361	42	0
	Mid risk	x	x	x	776	3	0	49	676	54	392	387	0
	High risk	x	x	x	135	505	173	7	137	669	38	531	244
Altman 2 Class	Low risk	403	776	135	x	x	x	311	879	124	773	538	3
	Mid risk	0	3	505	x	x	x	3	70	435	18	378	112
	High risk	0	0	173	x	x	x	5	1	167	0	44	129
FRB Category	Low risk	263	49	7	311	3	5	x	x	x	312	7	0
	Mid risk	137	676	137	879	70	1	x	x	x	474	476	0
	High risk	3	54	669	124	435	167	x	x	x	5	477	244
EBCSM Class	Low risk	361	392	38	773	18	0	312	474	5	x	x	x
	Mid risk	42	387	531	538	378	44	7	476	477	x	x	x
	High risk	0	0	244	3	112	129	0	0	244	x	x	x
Total		403	779	813	1314	508	173	319	950	726	791	960	244
Percent of sample		20%	39%	41%	66%	25%	9%	16%	48%	36%	40%	48%	12%

Table 4. Spearman Rank Correlation, Credit Classes, 1995 observations, 399 farms per year, 2000-04.

	Altman 1 Score	Altman 2 Score	FRB PD	EBCSM Score
Altman 1 Score	1.000	0.966	-0.863	-0.800
Altman 2 Score	0.966	1.000	-0.878	-0.790
FRB PD	-0.863	-0.878	1.000	0.862
EBCSM Score	-0.800	-0.790	0.862	1.000

Table 5. Mean Prediction Comparison Across Models: Base Period, 2000.

Rating Class 2000			2001-02 ENWGR	2001-02 TDRC	2002-03 ENWGR	2002-03 TDRC	2003-04 ENWGR	2003-04 TDRC
			mean values					
Altman 1 Class	Low risk	*a*	1.048% *bc*	397.396 *bc*	2.358% *c*	363.624 *bc*	3.989%	362.332 *bc*
	Mid risk	*b*	-0.522% *a*	24.552 *a*	1.647%	28.247 *a*	4.061%	31.353 *a*
	High risk	*c*	-0.867% *a*	7.161 *a*	1.091% *a*	7.533 *a*	3.589%	4.821 *a*
Altman 2 Class	Low risk	*a*	-0.059%	132.310 *bc*	1.881% *b*	124.629 *bc*	4.018%	126.187 *bc*
	Mid risk	*b*	-0.728% *c*	10.609 *a*	0.940% *a*	10.961 *a*	3.888%	1.860 *a*
	High risk	*c*	-1.571% *b*	0.718 *a*	0.957%	1.185 *a*	2.449%	16.382 *a*
FRB Category	Low risk	*a*	1.280% *bc*	479.322 *bc*	3.112% *bc*	427.204 *bc*	4.428%	399.383 *bc*
	Mid risk	*b*	-0.338% *a*	10.481 *a*	1.542% *a*	18.874 *a*	4.019%	30.965 *a*
	High risk	*c*	-1.192% *a*	4.372 *a*	0.817% *a*	4.779 *a*	3.353%	1.850 *a*
EBCSM Class	Low risk	*a*	0.557% *bc*	209.036 *bc*	2.243% *bc*	193.435 *bc*	4.535% *c*	193.304 *bc*
	Mid risk	*b*	-0.887% *a*	4.569 *a*	1.216% *a*	7.652 *a*	3.656%	10.132 *a*
	High risk	*c*	-1.445% *a*	11.128 *a*	0.543% *a*	11.747 *a*	2.301% *a*	1.545 *a*

ENWGR = Earned Net Worth Growth Rate, TDRC = Term Debt Repayment Capacity

Rating categories based on 2000 data.

Values are 2-year averages

abc values represent mean significant difference at 95% confidence level from respective group

Table 6. Classification Threshold Prediction Comparisons Across Models: Base Period, 2000.

Rating Class 2000			2001-02 ENWGR	2001-02 TDRC	2002-03 ENWGR	2002-03 TDRC	2003-04 ENWGR	2003-04 TDRC
			mean proportion of farms not exceeding stress threshold in respective year					
Altman 1 Class	Low risk	*a*	32.47% *bc*	12.99% *bc*	16.88% *c*	6.49% *bc*	6.49%	5.19% *bc*
	Mid risk	*b*	59.12% *a*	47.17% *a*	28.30%	30.82% *ac*	16.35%	16.98% *a*
	High risk	*c*	64.42% *a*	57.67% *a*	38.04% *a*	47.24% *ab*	14.11%	28.22% *a*
Altman 2 Class	Low risk	*a*	50.96% *c*	37.55% *bc*	26.05%	24.52% *bc*	13.79%	14.18% *c*
	Mid risk	*b*	62.86%	56.19% *a*	35.24%	40.95% *ac*	9.52%	20.95% *c*
	High risk	*c*	75.76% *a*	66.67% *a*	45.45%	72.73% *ab*	24.24%	54.55% *ab*
FRB Category	Low risk	*a*	31.88% *bc*	10.14% *bc*	13.04% *bc*	2.90% *bc*	7.25%	2.90%
	Mid risk	*b*	56.61% *a*	43.39% *a*	28.57% *ac*	29.10% *ac*	13.23%	15.34%
	High risk	*c*	67.38% *a*	63.83% *a*	40.43% *ab*	52.48% *ab*	17.02%	32.62%
EBCSM Class	Low risk	*a*	42.07% *bc*	21.95% *bc*	21.34% *bc*	15.24% *bc*	8.54% *c*	6.71% *c*
	Mid risk	*b*	63.64% *a*	58.82% *a*	33.16% *a*	40.11% *a*	15.51%	24.60%
	High risk	*c*	75.00% *a*	68.75% *a*	47.92% *a*	64.58% *a*	22.92% *a*	41.67% *a*

ENWGR = Earned Net Worth Growth Rate, TDRC = Term Debt Repayment Capacity

Rating categories based on 2000 data. Values indicate the proportion of farms not exceeding the minimum stress threshold values.

Threshold values ENWGR = 0%, TDRC = 1.0.

Values are 2-year averages.

abc values represent mean significant difference at 95% confidence level from respective group.

Figure 1. Repayment and Earnings Prediction Model: Altman Z Score Models

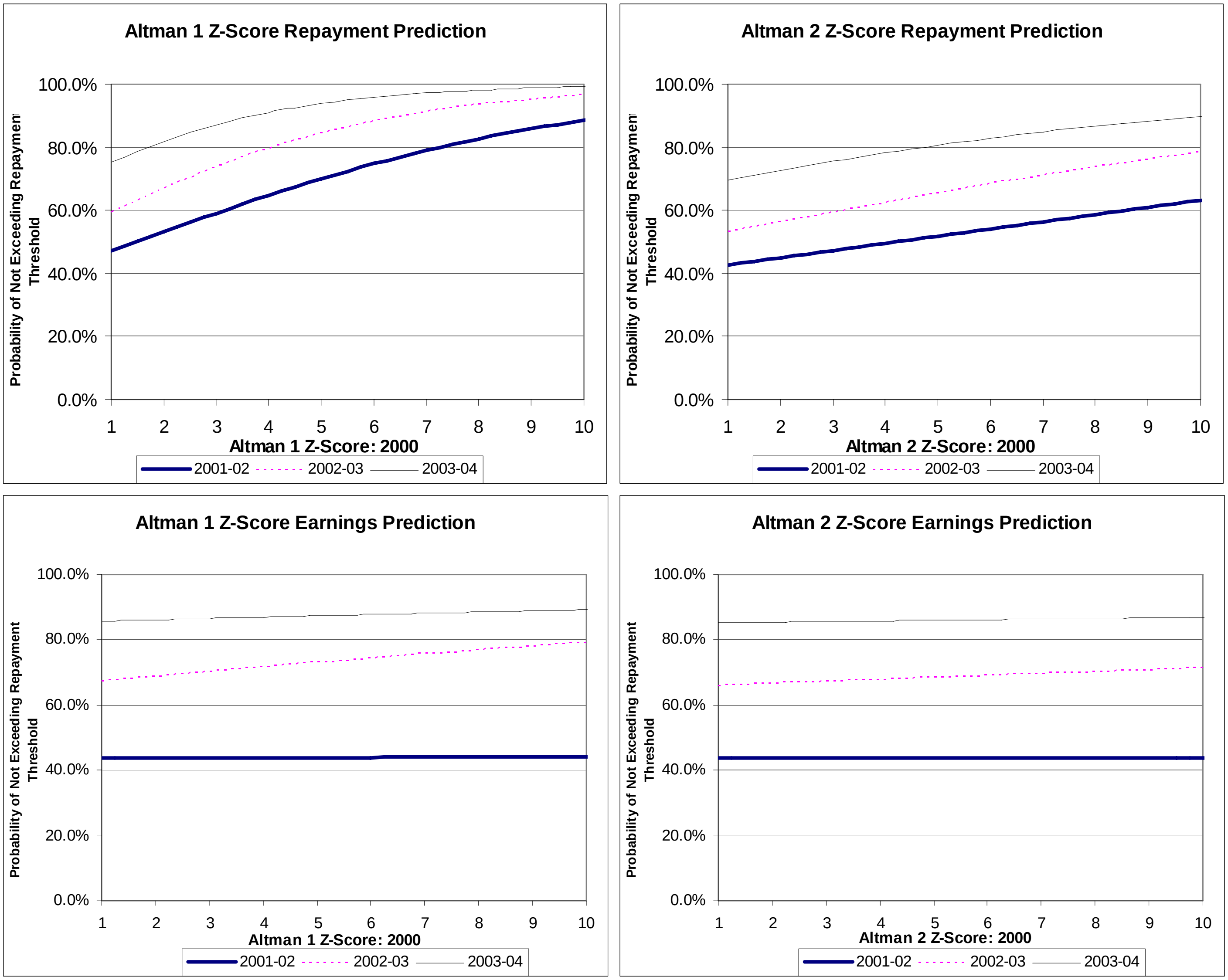

Figure 2. Repayment and Earnings Prediction Model: EBCSM and FRB PD Model