# Adapting Credit Risk Models to Agriculture

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**Abstract**

A framework is identified for modeling credit risk in agriculture. A CreditRisk+ type model is deemed most suitable for agricultural lending. The CreditRisk+ model is modified to overcome its drawbacks by incorporating recent research that accounts for sector correlations and uses a more stable and accurate algorithm. The model is applied to AgStar Financial Services, ACA, a cooperative agricultural lender, in order to determine how such a lender may adapt this model for portfolio risk analysis and to make capital and portfolio management decisions. The model generates a loan loss distribution, which is used to derive the lender's expected and unexpected losses for the overall portfolio and individual loans. The model shows that AgStar is more than adequately capitalized based on the parameters estimated using 1997-2002 data. Since AgStar's capital position is lower than that of most other associations, this raises the issue of overcapitalization within the Farm Credit System.

Key words: agricultural credit, value-at-risk, credit risk models, economic capital, portfolio risk analysis, capital adequacy, portfolio management.

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## Introduction

Applications of the modern portfolio management tools and concepts to agriculture are necessitated by overcapitalization and the need for better portfolio management in agricultural lending. Currently, the ratios of equity capital to assets for the combined Farm Credit System (FCS) banks and associations are well above minimum requirements, 15.25% at year-end 2000 (Barry, 2001, p. 116). High capital ratios reflect the Farm Credit System's orientation on safety in recovering from the stress of 1980s but do not represent clearly established targets or calibration of risk tolerances (Barry, 2001).

The new credit risk models allow portfolio managers to quantify risk at both the portfolio and individual loan contributory level, which was not possible before. The models are used to estimate a lender's probability density function for credit losses and to derive the amount of capital needed to support a lender's losses. Thus, they offer a more informed setting of limits and reserves and a more consistent basis for economic capital allocation. These models may help agricultural lenders identify more risk efficient levels of economic capital.

Agricultural lenders are limited in their opportunity to simply apply the sophisticated credit models that have been developed for large commercial banks. Data limitations presents a bigger problem for FCS institutions than for commercial banks, which can use comparable historical data collected by ratings agencies such as Moody's (Carty and Lieberman) or Standard & Poor's (Brand and Bahar). They cannot rely on access to financial market data (stock prices, external credit ratings, historic default rates and volatility measures, or other market information published by rating agencies) from which to assess client risk. Rather, they must find ways to adapt the principles of these models to manage their loan portfolios. Besides these data issues, agricultural lenders must insure that credit model assumptions and conceptual approaches are appropriate for modeling credit risk in agriculture. Credit models have not been adapted to agricultural lending at this point because they are relatively new and quite technical; so they are not easily accessible to many practitioners, such as associations in the Farm Credit System. Agricultural lenders tend to fall behind their commercial counterparts in the level of sophistication of portfolio management tools. They do not have as many resources for developing rigorous models as commercial banks because they are smaller institutions, and also because they reduced personnel in response to the crisis of 1980s to minimize costs.

In an effort to adapt credit risk tools to agricultural lending, this study has the following objectives:

1. To identify a credit risk model suitable for agricultural lenders.
2. To provide guidance to agricultural lenders on using the model to evaluate capital adequacy and to make portfolio management decisions.

The first objective includes examining the underlying assumptions and data needs of the existing credit risk models to analyze if they are suitable for modeling credit risk in agriculture. The most appropriate methodology is modified to adapt it to agricultural lending.

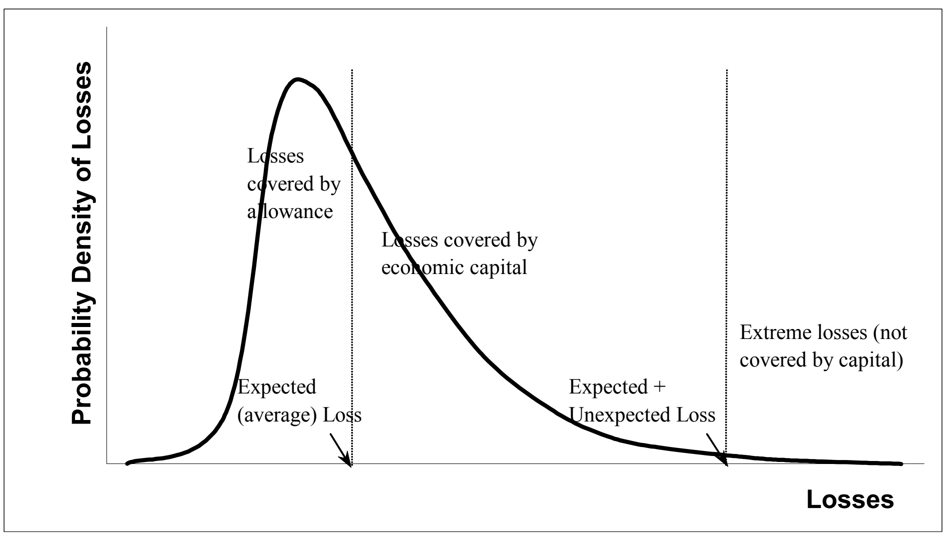
The second objective involves the application of the model to a representative Farm Credit System association, AgStar Financial Services, ACA. This objective includes appropriate parameterization of the model based on historical data consistently with the regulatory guidelines of the New Basel Capital Accord. The results show how an agricultural lender may adapt this model to evaluate capital adequacy and to conduct portfolio risk analysis.

**Loan Loss Characteristics**

Lenders hold capital to protect themselves from the risks arising from their portfolios. Lenders distinguish three different types of capital: book capital, regulatory capital, and economic capital. Book capital consists of shareholders' equity and retained earnings. Regulatory capital refers to the capital requirement under the Basel Capital Accord. Economic capital is defined in terms of the risk of the assets, both on-balance-sheet and off-balance sheet. It is a measure of the financial resources required to meet unexpected losses over a given period (usually one year) with a given confidence level, such as 99.5%.

Economic capital is to cushion unexpected losses due the overall risks of conducting business, which are usually categorized into credit, market and operational risks. Credit risk, the focus of this paper, is the primary source of risk for a lender. It is the risk of loss from borrower defaults. Credit risk includes borrower's creditworthiness, transaction structure, loan maturity, and concentration risk. Market risk occurs due to possible losses in market values of assets. Operational risk results from internal processes, people and systems or from external events such as legal risk, computer failures, fraud, poor monitoring. Operational risk is often defined very broadly, encompassing all risks that are not incorporated into credit or market risks. Most lending institutions compute total economic capital as a summation of economic capital allocations for each type of risk.

Figure 1: Probability Density Function of Loan Losses




This study focuses on estimating the distribution of portfolio loan losses due to credit risk. A loan loss distribution is pictured in Figure 1. It is characterized by a fat tail on the right, since low losses have a lower bound of zero, but large losses may occur with low probabilities.

Expected losses are long-run average losses; thus, they are accounted for in loan pricing and covered by the loan loss reserve (often referred to as allowance for loan losses). They are associated with the mean of the loan loss distribution pictured on Figure 1. The key risk characteristics (inputs) of expected loss (EL) are the probability of default (PD), loss given default (LGD), exposure at default (EAD), and time horizon. The expected loss of a loan can be calculated as the exposure at default adjusted for probability of default and loss given default, i.e.

EL = PD * LGD * EAD. Probability of default is the probability that a loss will occur over a given horizon. Loss given default is net of the recovery of losses in case of default. Both PD and LGD are usually represented in percentage terms. Exposure at default is the unpaid amount of loan at the time of default. The expected loss of a loan portfolio is equal to the sum of the expected losses of individual loans in the portfolio.

Unexpected losses are the maximum potential loss at a given level of confidence, usually 99 to 99.99 percent. One hundred minus the confidence level is often referred to as the insolvency rate. Unexpected losses are not accounted for in pricing, and they require economic capital to cover the loss with the target insolvency rate. Economic capital (see Figure 1) is the selected tail percentile representing total amount of risk finds (often referred to as Value-at-Risk) less the expected losses covered by the loan loss reserve.

Extreme losses are associated with the area under the loss curve above the 99 to 99.99% level of confidence (see Figure 1). Events falling into this area happen so rarely that it is too costly to hold capital to insure against them.

The probability density functions (PDF) of loan losses for the whole portfolio vary among different portfolios, but they “tend to be highly skewed and leptokurtic” (Ong, p. 163). The shape of portfolio PDF is dependent on the portfolio composition: loan default probabilities, relative loan sizes, correlations of default between loans, and concentration by industry. Unexpected losses of a portfolio are a lot smaller than the sum of the individual unexpected losses because of diversification effects (low or negative correlation among unexpected defaults of different borrowers). Only a portion of each loan's unexpected loss contributes to the portfolio's total unexpected loss. The incremental risk that a single loan contributes to the portfolio is called the risk contribution. It depends on the correlation of default of a given loan with other loans and represents undiversified risk of a loan in the portfolio.

**Basel Capital Accord**

The Basel Committee on Banking Supervision is proposing to introduce new risk-based requirements for internationally active and other significant banks by the end of 2006. These will replace the relatively risk-invariant requirements in the current Accord. Lenders will be allowed to choose between the standardized approach and the Internal Ratings-Based (IRB) approach, which can be either a "foundation" or "advanced" approach in the case of credit risk. Under the standardized approach, the previous uniform 100% risk weight for private obligors has been replaced by four weightings: 20%, 50%, 100%, and 150%, depending on the obligor’s risk rating. Under the foundation IRB approach, a bank develops its own PD for each borrower and relies on supervisory rules for the estimation of other risk components, LGD and EAD, which are calibrated using fairly conservative assumptions and historical data in commercial lending. Under the advanced IRB approach, bank develops its own estimates of PD, LGD, and EAD.

**Model Selection**

In the financial world, the four most prominent credit risk models are Portfolio Manager (KMV Corporation, released in 1993), CreditMetrics (RiskMetrics Group of J.P. Morgan, released in 1997), CreditRisk+ (Credit Suisse Financial Products, released in 1997), and CreditPortfolioView (McKinsey and Company, released in 1998). Table 1 shows the brief comparison of the models.

Table 1: Summary of Major Credit Risk Models

| | **Portfolio Manager** | **Credit Metrics** | **CreditPortfolio View** | **Credit Risk+** |
|---|---|---|---|---|
| Approach | Option-based | Option-based | Econometric | Actuarial |
| Definition of risk | MTM or DM | MTM | MTM or DM | DM |
| Risk drivers | Asset values | Asset values | Macro factors | Expected default rates |
| Data needs | Asset values, asset value volatilities | Credit spreads, yields for risk ratings, asset value volatilities | Economic factors driving default rates, borrower sensitivities to economic factors | Default rates, default rate volatilities |
| Correlation of credit events | Multivariate normal asset returns | Multivariate normal asset returns | Factor loadings | Correlation with expected default rate |

Recent studies conclude that the models described above are similar in the underlying structure and produce almost identical results when they are parameterized consistently and the models are correctly specified (Koyluoglu and Hickman; Gordy (2000); Finger).

Based on agricultural loan data availability and the ability to satisfy model assumptions, CreditRisk+ is the most appropriate model for agriculture. Compared to other credit risk models, CreditRisk+ also has advantages of requiring relatively few inputs and being relatively easy to implement and computationally attractive (Crouhy et al., p.113).

**CreditRisk+ Overview**

Credit Suisse Financial Products' (CSFP) model CreditRisk+[1] is based on the insurance approach that uses mortality analysis to model a sudden event of borrower default. No assumptions are made about the cause of default. Credit defaults occur as a sequence of events in such a way that it is not possible to forecast the exact time of any one default nor the exact total number of defaults. Default is modeled as a continuous random variable with a probability distribution. Default correlations in CreditRisk+ model are caused by background factors, such as the state of economy, which change the rates of default. Background factors may cause the incidences of default to be correlated, even though there is no causal link between them. Because the risk of default is assumed to fit certain distribution, it is possible to calculate the distribution of portfolio losses analytically.

[1] CreditRisk+ is a trademark of Credit Suisse Financial Products, a subsidiary of Credit Suisse First Boston. CreditRisk+ methodology is freely released to the public. CSFP's Internet site contains the technical document (CSFP) and a spreadsheet implementation of the model able to handle up to 4,000 exposures and 8 sectors.

Figure 2: Model Structure

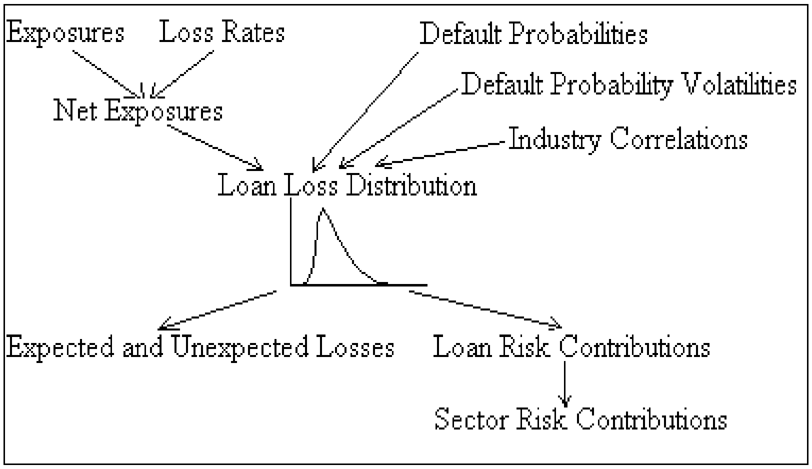



Figure 2 shows a brief overview of the model structure. The model inputs are exposures, default rates and their volatilities, and correlations of default between sectors (defined as industries in this study). The model inputs are exposures, default rates and their volatilities, and correlations of default between sectors (defined as industries in this study).

Since the release of the original model in 1997, several studies addressed various shortcomings of the model. Modifying the mathematical components of the model allows one to enhance the model to overcome its limitations while remaining within an analytical approach of the original model. This study improves the original CreditRisk+ model in two ways: by using an alternative algorithm that is more accurate, stable, and robust (according to Gordy, 2002), and by accounting for correlations between sectors (according to Bhrgisser et. al).

**Model Parameterization**

AgStar Financial Services, ACA (Agricultural Credit Association) is a member-owned cooperative that provides credit and credit-related services to eligible shareholders for qualified agricultural purposes. After a recent merger with Farm Credit Services of Northwest Wisconsin, AgStar's assets are $2.3 billion, and the number of clients is approximately 15,000. AgStar operates in 69 counties in Minnesota and northwest Wisconsin.

Capital is the equity or ownership of stockholders in the assets of the institution. Capital in associations is derived from two primary sources – investments by borrowers and retained earnings from operations. AgStar is well capitalized. On December 31, 2002, AgStar's permanent capital ratio (permanent capital divided by risk-weighted assets) was 12.1%, much greater than the required minimum of 7% (AgStar Financial Services, ACA). "Permanent capital" is defined as at-risk stock and surplus capital (retained earnings). AgStar's high capital ratios are lower than those of most other Farm Credit System lenders. For example, permanent capital ratios among the associations in the FCS Seventh district ranged from 11.8% to 34.4% and averaged 14.7% at December 31, 2002 (AgriBank, FCB and the Seventh District Associations).

AgStar's annual year-end data for 12/31/1997 – 12/31/2002 is used for deriving model parameters. The data is used to estimate economic capital requirements in 2003. The data includes various borrower, loan, and lease information. Loans and leases are collectively referred to as "loans" in the study.

Most of the parameters required by the model are the parameters required for the Internal Ratings-Based approach in the New Capital Accord. Basel recommendations for the IRB foundation approach for corporate exposures are used as guidance for the parameters where historical data is insufficient to provide precise parameter estimates.

*Default Probabilities and Their Volatilities*

Since a client's risk-rating grade represents his default probability, default probabilities and their deviations are calculated for each risk rating. Risk ratings range from highest quality (1) to loss (9). Acceptable risk ratings are 1 to 4, 5 is special mention, 6 to 8 are unacceptable ratings, and 9 is loss.

The New Capital Accord requires than all loans have a borrower risk rating assigned. However, AgStar currently does not require borrower risk ratings for clients with small loans. To insure that all loans have a risk rating, risk ratings are assigned to loans as follows: For the loans that have both customer risk rating and loan risk rating, customer risk rating is used (for 77.6% of loan volume). For the loans without customer-level risk rating, loan risk rating is used to approximate the borrower's probability of default (for 13.3% of loan volume). For the loans without customer and loan risk rating, the credit score is mapped into a risk rating using AgStar's guidelines (for 8.5% of loan volume). Finally, for the loans without any kind of risk rating or credit score, a risk rating of 3 is used, which assumes that these loans are of acceptable quality (for 0.5% of loan volume). This is consistent with AgStar practices when non-rated loans are assigned to Acceptable-3 classification (Wilberding, 1999).

The IRB approach in the New Capital Accord requires that "A bank must estimate a one-year probability of default for each of its internal rating grades" (Basel Committee on Banking Supervision, §270). Estimates of PD must represent a conservative view of a long-run average PD. AgStar' s data is sufficient to satisfy Basel's requirement of the minimum of 5 years of historical observations to estimate probability of default.

Table 2: Actual and Fitted Default Probabilities and Their Standard Deviations by Risk Rating

| Risk Rating | PD Historical | St. Dev. Historical | PD Smoothed | St. Dev. of PD Smoothed |
|---|---|---|---|---|
| **1** | 0.118% | 0.072% | 0.169% | 0.127% |
| **2** | 0.518% | 0.414% | 0.386% | 0.269% |
| **3** | 0.974% | 0.895% | 0.884% | 0.572% |
| **4** | 2.037% | 1.053% | 2.021% | 1.214% |
| **5** | 4.985% | 2.663% | 4.621% | 2.578% |
| **6** | 11.925% | 4.583% | 10.567% | 5.473% |
| **7** | 19.073% | 11.351% | 24.167% | 11.620% |
| **8** | 100.000% | 0.000% | 100.000% | 0.000% |
| **9** | 100.000% | 0.000% | 100.000% | 0.000% |
| **Mean (Rated)** | 1.529% | 0.523% | | |
| **Mean (Total)** | 1.224% | 0.373% | | |
| **Mean (Non-rated)** | 0.983% | 0.685% | | |

Using historical data series to calculate probabilities of default may be difficult, since annual frequency of observations does not allow for long time series. There may not be any defaults among obligors of high quality even in large samples. A zero default probability cannot be deduced from the fact that no defaults have been observed. A good way to estimate default probability for the risk ratings of highest quality that may not have any defaults in the sample and to smooth the estimates is to assume that default probability is a function of a risk rating. Default probabilities increase exponentially with the increase in risk ratings. This is a clue that a logarithmic transformation of the default probability is needed to fit a linear regression. After fitting OLS regression using the logarithm of PD as a response variable and risk rating as a predictor[2], an exponential function is estimated that is used to calculate smoothed default probabilities: Ln(PD) = -7.211+0.827 * Risk Rating. The smoothed values are reported in Table 2. Customers in risk ratings 8 and 9 are assigned default probability of 100% because all customers in these risk ratings are in default.

*Default Rate Volatility*

In Column 3 (Table 2) we report historical standard deviations of default rates. Standard deviations of default rates are modeled as a function of risk ratings. Standard deviations increase exponentially with risk ratings, similar to default probabilities. OLS regression is used to estimate the function: Ln(StDevPD) = -7.422 + 0.753 * Risk Rating.[3]

*Risk Migration*

The effect of risk migrations is included into the estimates of default rates and their volatilities.

Table 3: Average Annual Migration of Borrower Risk Ratings from 1997 to 2002

| **Rating** | **1** | **2** | **3** | **4** | **5** | **6** | **7** | **8** | **9** |
|---|---|---|---|---|---|---|---|---|---|
| **1** | 89.39% | 6.05% | 3.03% | 1.22% | 0.18% | 0.05% | 0.07% | | |
| **2** | 2.88% | 87.54% | 6.22% | 2.66% | 0.37% | 0.24% | 0.08% | | |
| **3** | 1.27% | 4.16% | 83.85% | 8.01% | 1.66% | 0.68% | 0.37% | | |
| **4** | 0.38% | 1.36% | 5.21% | 86.12% | 4.54% | 1.11% | 1.26% | | |
| **5** | 0.30% | 0.35% | 3.97% | 12.76% | 74.17% | 4.01% | 4.44% | | |
| **6** | | 0.33% | 1.36% | 9.53% | 2.25% | 82.08% | 4.46% | | |
| **7** | | | 0.20% | 5.57% | 1.07% | 3.72% | 89.45% | | |
| **8** | | | | | | | | | |
| **9** | | | | | | | | | |

Average historical risk-rating migrations are calculated based on annual AgStar's migrations in 1997-1998 through 2001-2002 (see Table 3). The first column shows customer risk rating in the beginning of the year. The other columns show the percentage of borrowers in each risk rating for the year-end. Only the customers that are not in default both in the beginning and

[2] There are no outliers, influential observations, or problems with heteroscedasticity. The regression has a very good fit with R-square of 0.98.

[3] There are no outliers, influential observations, or problems with heteroscedasticity. The regression has a very good fit with R-square of 0.95.

the end of year are included in the migrations. Defaulted customers are already accounted for in the calculations of default rates and their volatilities.

Since past risk rating migration patterns are expected to continue in the future, probabilities of default and their standard deviations are adjusted by migrations. Default probability adjusted for migration is the sum of fitted default probabilities for the risk ratings (see Table 2) weighted by the percentages of clients in the risk ratings at the end of the period (Table 3). For example, adjusted default probability for risk rating 1 is 0.169% * 0.8939 + 0.386% * 0.0605+ 0.884% * 0.0303 + 2.021% * 0.0122 + 4.621% * 0.018 + 10.567% * 0.005 + 24.167% * 0.007 = 0.257%. Default rate volatilities are adjusted in the same way.

Table 4: Probabilities of Default and their Standard Deviations Adjusted for Migrations and Used in the Model

| Risk Rating | PD Adj. | St. Dev. Adj. | PD Used | St. Dev. Used |
|---|---|---|---|---|
| **1** | 0.257% | 0.178% | 0.25% | 0.25% |
| **2** | 0.514% | 0.340% | 0.50% | 0.40% |
| **3** | 1.158% | 0.712% | 1.50% | 1.00% |
| **4** | 2.440% | 1.404% | 2.25% | 1.50% |
| **5** | 5.218% | 2.826% | 5.25% | 3.00% |
| **6** | 10.061% | 5.192% | 10.00% | 5.00% |
| **7** | 22.173% | 10.693% | 25.00% | 10.00% |
| **8** | 100.000% | 0.000% | 100.00% | 0.00% |
| **9** | 100.000% | 0.000% | 100.00% | 0.00% |

Adjusted probabilities of default and their volatilities are rounded for easier readability by model users (see Columns 4 and 5 in Table 4). Rounded default probabilities and their deviations are used as an input for the model.

*Loss Given Default*

Because of insufficient internal data to estimate LGD, the LGD rates in this study are based on the preliminary information from the Farm Credit System President's Commission on Credit Risk that adapts the New Basel Capital Accord to agricultural lending (Anderson). There are four different LGD grades (see Table 5). When AgStar assigns LGD ratings to all of its loans in the future, internally assigned LGD ratings should be used in the model to provide consistency between the parameters used for regulatory purposes and the model. In this study, the assignment of loans to LGD ratings is done in accordance with Farm Credit System proposed guidelines. The assignments are sufficiently conservative to reflect the risks of collateral volatility and exposure volatility.

Table 5: Loss Given Default Rates

| LGD Rating | % Loss Given Default |
|---|---|
| 1 | 3.00% |
| 2 | 20.00% |
| 3 | 50.00% |
| 4 | 75.00% |

LGD rating 1 is assigned to loans guaranteed by government agencies and to loans protected by credit derivatives. Loans with collateral-to-loan ratio over 150% are also included in this category. LGD rating 2 is assigned to loans with collateral-to-loan ratio between 100% and 150%. Leases are also included in this category since the leased assets are returned to the lender in the event of default. LGD rating 3 is assigned to loans with collateral-to-loan ratio between 50% and 100%. Short-term and intermediate-term loans without collateral information are also included in this category (unless they have LGD rating of 1 or 2). AgStar's database contains collateral information on these types of loans only if they are adversely classified, even though many loans of these types have ample collateral. Placing these loans in LGD rating 3 is viewed as a reasonably conservative assumption. LGD rating 4 is assigned to unsecured loans and to loans with collateral-to-loan ratios below 50%. In assigning LGD grades, collateral-to-loan ratios include the unfunded commitment.

*Sector Analysis*

Sectors usually represent industry/geographic region combinations in credit risk models. Since most of AgStar's portfolio is regionally concentrated in southern Minnesota and western Wisconsin, borrowers' industries are assumed to have the most impact on portfolio diversification. Consistent with AgStar internal practices and to insure that there is an adequate number of borrowers in each industry to estimate default probabilities by industry, customers are assigned to the following industries: crops (mostly corn and soybeans), general farms (primarily crop and this industry assigned by default to small loans), dairy, swine, other livestock (primarily cattle and poultry), landlord, rural residence, others (customers without an industry specified, agricultural businesses, and agricultural services). Correlations between industry default rates are estimated based on AgStar's historical data on default rates per industry over 1998-2002 (see Table 6).

Table 6: Correlations of Default Between Industries in AgStar Data

| | **Crops** | **Dairy** | **Swine** | **OtherLvst** | **Landlord** | **GenFarms** | **RuralRes** | **Others** |
|---|---|---|---|---|---|---|---|---|
| **Crops** | 1.00 | 0.67 | 0.70 | 0.96 | 0.39 | 0.04 | -0.80 | -0.38 |
| **Dairy** | 0.67 | 1.00 | 0.27 | 0.82 | -0.29 | -0.03 | -0.61 | -0.31 |
| **Swine** | 0.70 | 0.27 | 1.00 | 0.66 | 0.25 | -0.41 | -0.52 | -0.73 |
| **OtherLvst** | 0.96 | 0.82 | 0.66 | 1.00 | 0.13 | -0.12 | -0.86 | -0.51 |
| **Landlord** | 0.39 | -0.29 | 0.25 | 0.13 | 1.00 | 0.60 | -0.01 | 0.39 |
| **GenFarms** | 0.04 | -0.03 | -0.41 | -0.12 | 0.60 | 1.00 | 0.39 | 0.90 |
| **RuralRes** | -0.80 | -0.61 | -0.52 | -0.86 | -0.01 | 0.39 | 1.00 | 0.63 |
| **Others** | -0.38 | -0.31 | -0.73 | -0.51 | 0.39 | 0.90 | 0.63 | 1.00 |

Based on the correlation structure, there appears to be two independent groups of industries. The first group represents the traditional farm economy and includes crops, dairy, swine, and other livestock. Defaults in these industries are positively correlated. The second group represents the general economy and includes rural residence, general farms (industry assigned by default to small loans usually given to part-time farmers), and others. Default probabilities across these industries are also positively correlated. Default probabilities are negatively correlated between the "traditional farm" industries and the "general economy" industries. Defaults in the landlord industry are somewhat correlated with some of the both traditional farm industries and the general economy industries. The landlord industry is correlated with crops, general farms, and "others" industry. This is an expected result, since landlords usually receive most of their income from renting land to crop farmers and part-time farmers, so they are affected by both farm economy and general economy.

The presence of two independent groups of industries representing the traditional farm economy and the general economy is the evidence that the economic cycle in agriculture is independent of the economic cycle in the general economy. Longer data series would be necessary to confirm this result with a higher accuracy.

Since the model is not designed to handle negative correlations, industries where probabilities of default are negatively correlated are assumed to be independent (have zero correlation), resulting in a slight conservative bias of the resulting economic capital requirements. Replacing negative correlations with zeros and rounding AgStar's internal correlation data, the correlations in Table 7 are obtained. This correlation structure is used in the study.

Table 7: Correlations of Default Between Industries Used in the Model

| | **Crops** | **Dairy** | **Swine** | **OtherLvst** | **Landlord** | **GenFarms** | **RuralRes** | **Others** |
|---|---|---|---|---|---|---|---|---|
| **Crops** | 1.0 | 0.7 | 0.7 | 0.9 | 0.4 | 0.0 | 0.0 | 0.0 |
| **Dairy** | 0.7 | 1.0 | 0.3 | 0.8 | 0.0 | 0.0 | 0.0 | 0.0 |
| **Swine** | 0.7 | 0.3 | 1.0 | 0.7 | 0.0 | 0.0 | 0.0 | 0.0 |
| **OtherLvst** | 0.9 | 0.8 | 0.7 | 1.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| **Landlord** | 0.4 | 0.0 | 0.0 | 0.0 | 1.0 | 0.6 | 0.0 | 0.4 |
| **GenFarms** | 0.0 | 0.0 | 0.0 | 0.0 | 0.6 | 1.0 | 0.4 | 0.9 |
| **RuralRes** | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.4 | 1.0 | 0.6 |
| **Others** | 0.0 | 0.0 | 0.0 | 0.0 | 0.4 | 0.9 | 0.6 | 1.0 |

*Market and Operational Risks*

Since the Farm Credit System does not have any rules on estimating capital for operational risk, the recommendations of the New Basel Capital Accord are used. The simplified standardized approach for operational risk is the Basic Indicator Approach (applicable to any bank regardless of its complexity or sophistication), under which banks must hold capital equal to a fixed percentage (15%) of average annual gross income over the previous three years (Basel Committee on Banking Supervision, p.94). Annual gross income based on AgStar's 2002 Annual Report is about $158,401,300, which makes operational risk capital 0.87% of the gross exposure.

Since associations do not have trading book, foreign exchange risk and commodity price risk exposures, they are not required to hold market risk capital according to the Basel regulations. AgStar is protected from interest rate risk, since it borrows from AgriBank to fund its lending operations. Thus, there is minimal market risk capital required. Since the operational risk capital is estimated to be 0.87% of the gross exposure, the market risk capital is taken to be 0.13% of the gross exposure for simplicity, to make the sum of operational risk capital and market risk capital equal to 1% of the gross exposure, or $26,083,431.

**Model Results**

The main result of the credit risk model is the loan loss distribution. All model outputs are based on the loan loss distribution. Table 8 shows the summary of the analyzed portfolio and the summary of the resulting loan loss distribution. Throughout the study, all exposures, losses, and percentiles are given in dollar amounts.

Table 8: Loan Loss Distribution Summary

| **Summary Data** | |
|---|---|
| Total No. of exposures | 28,662 |
| No. of nondefaulted exposures | 28,330 |
| Total volume | 2,608,343,079 |
| Maximum loss | 786,365,777 |
| **Loan Loss Distribution Characteristics** | |
| Mean | 12,781,624 |
| Standard deviation | 6,909,614 |
| Skewness | 1.11 |
| Kurtosis | 4.80 |
| 90th percentile | 32,522,867 |
| 99th percentile | 44,594,626 |
| 99.99th percentile | 65,615,834 |

Total exposure is the sum of individual exposures including unfunded commitments weighted at 75%. Maximum loss is the sum of exposures multiplied by LGD rates. The distribution mean is the expected loss on non-defaulted loans. Tail percentiles show the Value-at-Risk, the total required risk funds to cover expected losses and unexpected losses.

*Capital Adequacy*

The mean of the distribution, or expected loss, represents allowance requirements. In the Basel 1988 Accord, it was agreed that allowance could be recorded as capital against requirements. Thus, the difference between Value-at-Risk at the selected percentile (such as 99.97%) and the mean is credit risk capital. Since the establishment of the allowance impacts the level of capital, the adequacy of allowance should be established first (FCA). Expected losses on defaulted loans are added to the expected losses on non-defaulted loans to arrive at the required allowance for loan loss in Table 9.

Table 9: Allowance for Loan Loss

| **Expected Losses on** | | **% Exposure** |
|---|---|---|
| **nondefaulted loans** | 12,781,624 | 0.49% |
| **+ defaulted loans** | 10,398,970 | 0.40% |
| **= Allowance** | 23,180,594 | 0.89% |

Charge-offs on defaulted loans should be counted against the required allowance since they are actual losses, not expected losses. Actual losses are already paid out of allowance. Alternatively, charge-offs on defaulted loans can be added to the actual allowance to arrive at the same difference between actual and required allowance. AgStar’s book allowance is $42,402,000. Adding charge-offs on defaulted loans brings allowance to about $46,000,000. This exceeds (by twice) the required allowance under chosen parameterization.

Table 10: Economic Capital Under Various Confidence Levels

| Loss Percentile | CreditRisk ValueAtRisk | Allowance | Credit Risk Capital | % RWA | Mrkt&Oper. Risk Capital | Economic Capital | % RWA |
|---|---|---|---|---|---|---|---|
| **Col. 1** | **Col. 2** | **Col. 3** | **Col. 4** | **Col. 5** | **Col. 6** | **Col. 7** | **Col. 8** |
| 90.00% | 32,522,867 | 23,180,594 | 9,342,273 | 0.42% | 26,083,431 | 35,425,704 | 1.59% |
| 95.00% | 36,362,992 | 23,180,594 | 13,182,398 | 0.59% | 26,083,431 | 39,265,829 | 1.77% |
| 97.00% | 39,065,658 | 23,180,594 | 15,885,064 | 0.71% | 26,083,431 | 41,968,495 | 1.89% |
| 98.00% | 41,142,301 | 23,180,594 | 17,961,708 | 0.81% | 26,083,431 | 44,045,138 | 1.98% |
| 99.00% | 44,594,626 | 23,180,594 | 21,414,032 | 0.96% | 26,083,431 | 47,497,463 | 2.14% |
| 99.50% | 47,944,787 | 23,180,594 | 24,764,193 | 1.11% | 26,083,431 | 50,847,624 | 2.29% |
| 99.90% | 55,420,110 | 23,180,594 | 32,239,516 | 1.45% | 26,083,431 | 58,322,947 | 2.62% |
| 99.95% | 58,528,006 | 23,180,594 | 35,347,412 | 1.59% | 26,083,431 | 61,430,843 | 2.76% |
| **99.97%** | **60,834,934** | **23,180,594** | **37,654,340** | **1.69%** | **26,083,431** | **63,737,771** | **2.87%** |
| 99.99% | 65,615,834 | 23,180,594 | 42,435,240 | 1.91% | 26,083,431 | 68,518,671 | 3.08% |

The loan loss distribution allows for the comparison of economic capital at various confidence levels to the existing risk funds (Table 10). Typical confidence levels range from 99.00% to 99.99%. The choice of the confidence level depends on the lender's level of risk aversion. The choice of the confidence level selected by a financial institution with rated debt depends on the target debt rating. For example, a 99.90% capital level corresponds to a single-A rating. The New Basel Capital Accord uses 99.50$^{th}$ percentile in deriving the regulatory function. The 99.97$^{th}$ percentile is used by many commercial banks, and it is used as a primary confidence level in this study. This confidence level means that AgStar would incur losses greater than economic capital in one out of 3,000 years under the given parameterization.

Table 10 (Column 2) shows Value-at-Risk (required total risk funds to cover losses at a given loss percentile). Credit risk capital is Value-at-Risk less allowance. Economic capital needs to cover market and operational risks in addition to credit risk. The sum of credit risk capital and market and operational risk capital is total economic capital. Total economic capital (Column 7) can be compared with the lender's book capital. Economic capital as a percent of Risk-Weighted Assets (RWA) (Column 8) can be compared against the 7% permanent capital ratio requirement. Risk-weighted assets are $2,222,644,152. Table 10 shows that the choice of confidence level is an important parameter. The amount of economic capital nearly doubles as the confidence level increases from 90.00% to 99.99%.

Table 11 shows the comparison of economic capital to the book capital under the 99.97$^{th}$ loss percentile. Economic capital is $63,737,771, much less than the book capital of $269,829,000. Unallocated surplus is $240,938,000, also significantly exceeding economic capital.

Table 11: Comparison of Economic Capital at 99.97th Percentile to Book Capital

| | % RWA | Risk Capital | % Total Capital |
|---|---|---|---|
| Credit Risk Capital | 1.69% | 37,654,340 | 59.08% |
| Operational & Market Risk Capital | 1.17% | 26,083,431 | 40.92% |
| Total Economic Capital | 2.87% | 63,737,771 | 100.00% |
| Current Book Capital | 12.14% | 269,829,000 | |
| Current Capital Margin | 9.27% | 206,091,229 | |
| Allowance for Losses | 1.04% | 23,180,594 | |
| Current Book Allowance | 1.91% | 42,402,000 | |
| Allowance Margin | 0.86% | 19,221,406 | |
| Total Risk Funds | 3.91% | 86,918,365 | |
| Current Book Risk Funds | 14.05% | 312,231,000 | |
| Risk Funds Margin | 10.14% | 225,312,635 | |

In an efficient market, book capital should be the minimum of regulatory and economic capital. Regulators would not allow the level of capital below the regulatory capital requirement, while the market would not allow the book capital below economic capital requirements (Falkenstein, p. 2). Holding excess economic capital is not optimal since the lender could increase its returns by taking on risky projects where economic requirements are greater than the regulatory requirements because the marginal capital cost is zero in such cases (Falkenstein, p. 10).

Under selected parameters, AgStar holds more than three times as much capital as the model requires. One may think that AgStar holds excessive economic capital, and it should reduce its book capital to the 7% permanent capital ratio. It is important to remember that probabilities of default and their standard deviations were calculated based on the last five years, which were comparatively favorable for the agricultural economy. Ideally, these parameters should be averages over at least one economic cycle. Stress-testing (covered later) is necessary to analyze the effects of economy deterioration on the economic capital requirements. The Basel Capital Accord recommends that capital be sufficient in the event of at least a mild recession. The Farm Credit System would like to see associations being able to withstand the stress compatible to the stress of 1980s[4].

*Stress-Testing*

Stress-testing gauges potential vulnerability of financial institutions to probable and exceptional but plausible events. Stress-testing is widely used as a supplement for Value-at-Risk models (Committee on the Global Financial System, p. 2). Stress-testing is a way of measuring and monitoring the consequences of extreme movements in parameters. Value-at-Risk is of limited use in measuring exposures to extreme market events because, by definition, such events happen too rarely to be captured by empirically driven statistical models (Committee on the Global Financial System, p. 2).

[4] Based on the opinions of AgriBank management staff.

Stress-testing scenarios show the effects of changes in several parameters reflecting events that can be historical or hypothetical, probable or extreme. Stress-testing scenarios are required by the New Basel Capital Accord (Basel Committee on Banking Supervision).

Table 14 shows model results under various historical and hypothetical scenarios. Model parameters are returned to their basic values after analyzing each scenario. Loans that are in default are assumed to remain in default. Allowance, economic capital, and total risk funds margin are shown as dollar amounts and percentages of Risk-Weighted Assets (RWA) under various scenarios. Risk Funds Margin (column 6) shows excess of book risk funds (if positive) or shortage of book risk funds (if negative). All of the scenarios are analyzed under 99.97$^{th}$ confidence level.

Table 14: Stress-Testing at 99.97th Percentile

| Scenario | Allowance | % RWA | Econ. Capital | % RWA | RiskFundsMargin | %RWA |
|---|---|---|---|---|---|---|
| Basic | 23,180,594 | 1.04% | 63,737,771 | 2.87% | 225,312,635 | 10.14% |
| Mild Recession 1 | 29,499,473 | 1.33% | 74,120,475 | 3.33% | 208,611,052 | 9.39% |
| Mild Recession 2 | 35,962,218 | 1.62% | 88,799,807 | 4.00% | 187,468,974 | 8.43% |
| Simple Implement. | 23,180,594 | 1.04% | 124,005,906 | 5.58% | 165,044,500 | 7.43% |
| Moder. Recession | 60,456,152 | 2.72% | 118,069,215 | 5.31% | 133,705,632 | 6.02% |
| Zero Recovery | 86,417,254 | 3.89% | 136,798,883 | 6.15% | 89,014,863 | 4.00% |
| Severe Recession | 92,102,402 | 4.14% | 189,342,480 | 8.52% | 30,786,118 | 1.39% |
| Crisis of 1980s | 129,274,260 | 5.82% | 472,610,785 | 21.26% | -289,654,045 | -13.03% |

The “Basic” scenario repeats the results described earlier in the chapter under the chosen parameters. To simulate the effect of a recession, one can shock probabilities of default, their standard deviations, and LGD rates in the following two ways. The first way is to change probabilities of default and their standard deviations for each risk rating, and to change LGD rates for each LGD rating. The second way is to migrate clients to lower risk ratings and LGD ratings, keeping default probabilities and recovery rates the same for each rating. The two approaches can be combined. The choice can reflect the definition of default probability and recovery rate: point-in-time or through-the-cycle, or simply be the choice that is easier to understand.

"Mild Recession 1" scenario assumes that 50% of risk ratings and LGD ratings migrate to the next lower rating, representing the fact that risk ratings may migrate downward, and collateral values may decline or collateral may become less liquid during a recession. Thus, half of the loans risk rated 1 become risk rated 2, half of the loans risk rated 2 become risk rated 3, etc. "Mild Recession 2" scenario shows the situation when all probabilities of default and their standard deviations double, which can also be representative of a mild recession. Both Mild Recession scenarios do not have much effect on the risk funds margin, decreasing it only from 10% to 8-9% of risk-weighted assets.

The "Simple Implementation” scenario shows model results under conservative assumptions made in calibrating the model. The author of CreditRisk+, Wilde (2000), states that "A simple but robust implementation of CreditRisk+ is to use one sector, and assume that the default rate volatility for each borrower is about 100% of its mean" (p. 613). This is a conservative implementation of the model that may be preferred under the absence of reliable industry correlation structure and default rate volatilities. Assuming 100% correlation between defaults in all industries and standard deviations of 100% of the mean default probabilities doubles the amount of economic capital, having more effect on capital adequacy than a mild recession. It reduces the risk funds margin from 10% to 7% of risk-weighted assets.

The "Moderate recession" scenario assumes that all risk ratings and LGD ratings migrate downward by 2 ratings. Thus, all loans that are risk rated 1 become risk rated 3; all loans that are risk rated 2 become risk rated 4; etc. Under this scenario, risk funds margin decreases to 6% of risk-weighted assets.

“Zero Recovery” scenario reflects the situation when Loss Given Default is 100% for all the loans. This can be the case when collateral assets devalue and/or market becomes so illiquid that collateral cannot be recovered in a reasonable time period. This scenario increases total risk funds in 2.5 times. Risk funds margin shrinks to 4% of risk-weighted assets.

“Severe recession” scenario assumes that default probabilities and their standard deviations triple, and loss given default rates double. The scenario increases the need for risk funds over the three times compared to the basic scenario. Book risk funds are still sufficient to withstand the increased risk in the portfolio at the 99.97% confidence level, having risk funds margin of over 1% of risk-weighted assets.

“Crisis of 1980s” scenario assumes that default probability and its standard deviation is 10% for loans in all risk ratings, reflecting the fact that in Minnesota, 24% of commercial farms faced default in 1984-86, and 10% were technically insolvent (Hanson et. al.) in the absence of more detailed information. The scenario assumes that LGD rates increase by 50% for all LGD ratings (LGD for rating 4 is capped at 100%) reflecting the fact that land values declined by about 50% during 1981-87 (Hanson et. al.). The book risk funds show significant shortage under this scenario at the 99.97$^{th}$ percentile. However, the funds are still sufficient under the 95$^{th}$ percentile (shortage of funds in one out of 20 years). Considering that a crisis similar to the one of 1980s lasts less than 20 years, AgStar may have sufficient funds to withstand a similar event.

Overall, stress-testing under the chosen parameters shows that AgStar is adequately capitalized to withstand a recession, even a severe one or a farm financial crisis.

## Conclusions

This research makes a significant contribution to the existing literature on credit risk assessment and the tools that are available for evaluating credit risk exposure in the Farm Credit System. It also provides a new practical perspective on the issue of capital adequacy. The credit risk model improves the overall ability to identify, measure and manage credit risk. A lending institution may use the model to: forecast losses, identify allowance and capital requirements, evaluate risk-adjusted profitability for the overall portfolio, various subportfolios and individual loans, price loans, manage portfolio risk and monitor it over time, set risk-based concentration limits, forecast effects of portfolio growth, analyze the effects of changes in portfolio composition, diversification, and various hypothetical or historical scenarios that affect credit quality.

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