Evaluating Credit Risk Exposure in Agriculture

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Abstract

The thesis adapts loan portfolio management tools to agricultural lending and provides guidance on appropriate capital allocation and portfolio management using the tools.

A framework is identified for modeling credit risk in agriculture. The components and methodologies of major credit risk models in commercial lending are analyzed in relationship to credit risk in agricultural lending. A CreditRisk+ type model is deemed most suitable for agricultural lending, since the data requirements of that model can be satisfied by the available data and the assumptions are appropriate for modeling credit risk in agriculture. 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. AgStar data and Farm Credit System regulatory guidelines are used to determine model parameters, such as exposures, probabilities of default and their volatilities, recovery rates in the event of default, and correlations between industry types. 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 study shows how model results can be used for the following purposes: evaluating loan portfolio capital adequacy for both the allowance for loan loss and capital; identifying the allowance for loan loss and economic capital requirements for

each portfolio segment (by industry/loan type/risk rating/etc.) to analyze loan concentration risk and set credit limits; monitoring loan concentrations and loan portfolio risk over time; studying the effect of changes in the loan portfolio composition on allowance and capital requirements; stress-testing the loan portfolio; and analyzing risk-adjusted profitability.

The model shows that AgStar is more than adequately capitalized based on the parameters estimated using 1997-2002 data. AgStar's capital position is lower than that of most other FCS associations. This raises the issue of overcapitalization within the Farm Credit System.

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Abbreviation	Meaning	Page
BRW	Benchmark Risk Weight	21
CGF	Cumulant Generating Function	73
CLF	Commercial Lending Facility	40
CSFP	Credit Suisse Financial Products	61
DM	Default Mode	47
EAD	Exposure At Default	13
EL	Expected Loss	13
EMV	Estimated Market Value	118
EVA	Economic Value Added	17
FCA	Farm Credit Administration	31
FCS	Farm Credit System	31
IRB	Internal Ratings-Based	20
LGD	Loss Given Default	13
MTM	Mark-to-Market	47
NRV	Net Realizable Value	118
PD	Probability of Default	43
PDF	Probability Density Function	14
PGF	Probability Generating Function	68
RAROC	Risk-Adjusted Return on Capital	16
RR	Risk Rating	99
RW	Risk Weight	21
RWA	Risk-Weighted Assets	19
SLPM	Strategic Loan Portfolio Management	35
SUR	Seemingly Unrelated Regressions	83
VaR	Value-at-Risk	9

CHAPTER 1

INTRODUCTION

Applications of modern portfolio management tools and concepts to agriculture are necessitated by overcapitalization and the need for better portfolio management in agricultural lending. Agricultural lenders are limited in their ability to simply apply commercial credit risk models because they have different clientele and limited historical data. These models are also relatively new and quite technical; thus they are not easily accessible to practitioners. The purpose of this study is to adapt modern credit risk models to agricultural lending to determine capital adequacy and to identify, measure, and manage portfolio credit risks.

1.1 Introduction

Deterioration of the financial conditions in agriculture has been the topic of news reports and research efforts for some time. Farmers and agribusinesses are facing increased uncertainties, as are the lenders that provide their financing. The revenue uncertainties are caused by low and unstable commodity prices. Evaluating a portfolio of agricultural loans has become an important issue in recent years primarily due to the large number of farm failures and loan defaults among borrowers and, as a consequence, bank failures. Thus, the need for effective, proactive loan portfolio risk management is deemed essential for lender survival in the current era of declining and uncertain farm prices and volatile interest rates.

Lenders have traditionally viewed credit risk management as transaction management. The idea was if the lender did a good job of selecting, underwriting, documenting, and monitoring individual transactions, the lender would achieve a quality loan portfolio. Unfortunately, transaction management is not sufficient when the lender allows concentration to build in the portfolio (Barrickman, Bauer, and McKinley).

The concentration risk of a loan portfolio is the risk that individual loans may default at the same time due to the impact of common factors. Concentrations are considered a measure of the degree of co-movement in unexpected loan losses. Quantitatively, concentrations are correlations between probability distributions of loan losses. A portfolio's risk exposure cannot be determined without accounting for risk concentrations. Ignoring the correlations in a loan portfolio can lead to an underestimation of the overall portfolio risk by almost one-half (Kao and Kallberg, p.19). This form of underestimation of portfolio risk results in an increased possibility of severe losses that exceed a bank's capital and in a decrease of bank returns due to loan underpricing.

The Basel Committee for Banking Supervision (described in later sections) emphasizes the importance of diversification and indicates that one of the main reasons behind bank failures is inappropriate credit concentrations. These actions of regulators can be considered as "wake-up calls" to bank management: "Bankers blamed losses on the economy, but a more accurate assessment would suggest that management failed in its risk management responsibilities" (Lula, p.15). The Basel Capital Accord intends to strengthen (and make more uniform) the capital requirements for large internationally active banks. The Basel Accord "became a standard for adaptation and use by regulatory agencies with other banks and other types of financial institutions (including, for example, the U.S. Farm Credit System)" (Barry, 2001, p.110).

After suffering losses from high concentrations, many agricultural lenders increased the levels of their capital allocated to unexpected losses instead of reducing portfolio risk through active portfolio management. Currently, the ratios of equity capital to assets for the combined Farm Credit System 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). Currently, more attention needs to be given to how much capital is really needed.

Establishing the optimal level of economic capital (capital to cushion unexpected losses) is necessary for a lending institution to maximize profits. Since capital is a scarce resource, overly conservative estimates of economic capital make the lender lose the higher rate of return that could be earned if the capital was used for lending purposes. Too low estimates of economic capital, on the other hand, subject the lender to a higher level of risk than the institution can bear.

In recent years, important advances have been made in measurement, monitoring and management of credit risk in lending portfolios of large commercial banks. This research was motivated by the increase in bankruptcies worldwide, more competitive margins on loans and decline in the average quality of loans due to expansion of capital markets, advances in information technology and finance theory and, most importantly, the regulations set by the Basel Committee for Banking Supervision.

The New Basel Capital Accord gives banks an option to develop "internal model" approaches to measuring credit risk of a loan and loan portfolios and use them to determine their own capital requirements instead of being subjected to the inflexible 8% capital requirement imposed by the 1988 Basel Accord (Basel Committee of Banking Supervision, 2001). Much of the research in this area is relatively new, having started in 1990s.

The new credit risk models allow portfolio managers to quantify risk at both the portfolio and 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.

Economic capital allocations are used to measure risk-adjusted profitability to ensure that equity is used as efficiently as possible. Economic capital allocation process may be used in loan pricing to insure that the expected return on capital for new loans exceeds the hurdle rate for the lender. This may contribute to a more transparent decision-making process and more accurate risk- and performance-based pricing. Customer credit limits and portfolio concentration limits can be set. Economic capital allocations can also be used for active portfolio risk management to achieve a more preferred risk-return position.

Agricultural lenders are limited in their opportunity to simply apply the sophisticated credit models that have been developed for large commercial banks. 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.

1.2 Objectives

In an effort to adapt credit risk tools to agricultural lending, this dissertation 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 consistent 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.

This dissertation proceeds as follows. First, it presents a literature review in Chapter 2. It includes the overview of concepts behind credit risk models, regulatory motives for their implementation, and their advantages over traditionally used methods. Chapter 3 describes the data used in the study. Chapter 4 discusses the methodology issues, such as components of credit risk models and the major credit risk models, in relationship to credit risk in agriculture. Chapter 5 develops the model by enhancing the most appropriate credit risk methodology using latest research, and determines model implementation issues. Chapter 6 estimates model parameters based on AgStar's data and regulatory guidelines. Chapter 7 presents model results and explains how they can be used for portfolio risk management. Finally, Chapter 8 presents conclusions and implications for agricultural lenders.

CHAPTER 2

LITERATURE REVIEW

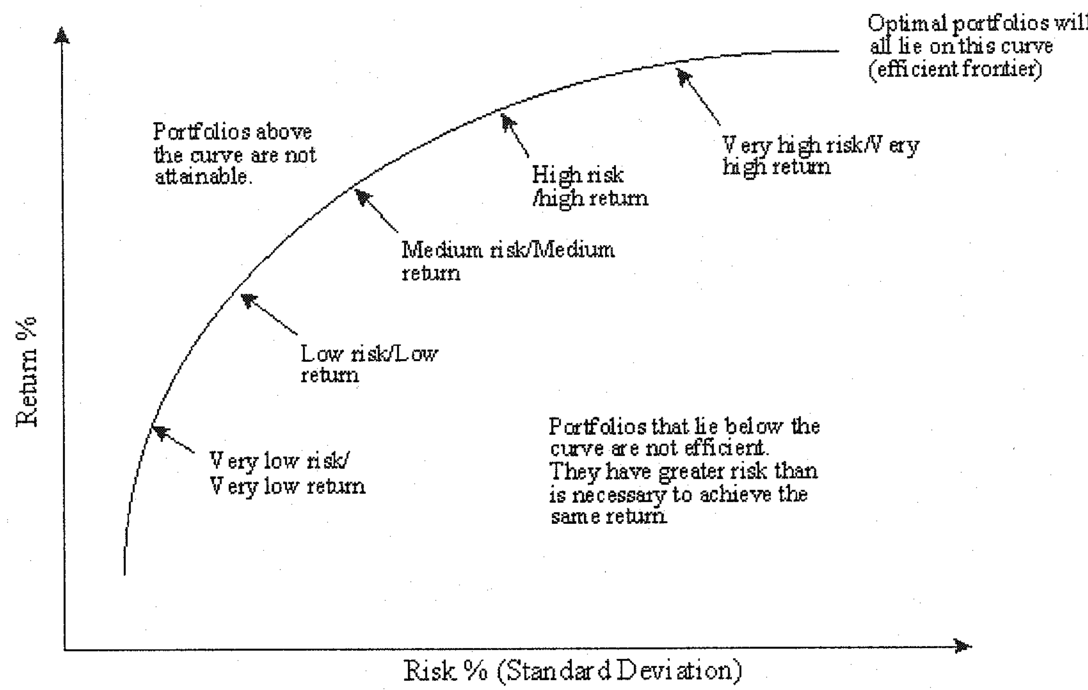
The first part of this chapter explains how the principles of credit risk models relate to the literature on portfolio optimization. The second part gives an overview of the concepts related to the risk in loan portfolios and the relationship between portfolio risk and lender's capital that serves as a buffer against the risk. The third part covers upcoming capital requirements set by the Basel Committee on Banking Supervision, their relation to credit risk models, and implications for agricultural lenders. The final part describes the current state of credit risk modeling in agriculture and explains how it can be improved by using modern credit risk models.

2.1 Value-at-Risk as a Tool for Portfolio Optimization

Basic portfolio theory was originated by Harry Markowitz (Nobel Prize winner) in the early 1950's. Markowitz quantified portfolio risk and showed how portfolio diversification works to reduce risk for investors. Modern Portfolio Theory explores how risk-averse investors construct portfolios in order to optimize risk against expected returns. Out of a universe of risky assets, an efficient frontier of optimal portfolios can be constructed. Each portfolio on the efficient frontier offers the maximum possible expected return for a given level of risk, or the minimum possible risk for a given level of return (see **Figure 2.1**).

The efficient frontier is concave because the risk and returns combinations of all assets in the portfolio result in returns that are the weighted average of the asset returns but the risk is less than the weighted average due to the contribution of covariance factors. Typically, the portfolios that comprise the efficient frontier are the ones that are most highly diversified. Less diversified portfolios tend to be closer to the middle of the achievable region.

Figure 2.1: Efficient Portfolio Frontier



Source: http://moneyonline.co.nz/calculator/theory.htm

Agricultural lenders are able to move closer to the efficient frontier by diversifying their portfolios and also by adequately pricing loans and insuring appropriate risk-return relationship for each loan in the portfolio. The optimal point on the risk-return frontier depends on the risk preferences of agricultural lenders. These preferences, on one hand, are affected by the regulators who would like to minimize the risk, and on the other hand, by shareholders who favor higher returns. Lenders can modify their portfolio risk-return trade-offs by making new loans, selling existing loans, and using derivatives and participations.

Modern Portfolio Theory states that the risk in a portfolio can be approximated by the portfolio standard deviation. This measure has some drawbacks when applied to loan portfolios. First, managers think of risk in terms of dollars of loss, while standard deviation defines risk in terms of deviations from expected return. Thus, it is not intuitive. Second, the use of standard deviation assumes symmetric (usually normal) distribution, while the distributions of returns in loan portfolios are skewed.

An alternative measure of risk, Value-at-Risk (VaR) overcomes these disadvantages. VaR provides a single number that encapsulates information about the risk in a portfolio and could communicate that information to nontechnical managers. VaR measures portfolio risk by estimating the loss associated with a given, small probability of occurrence. Higher risk means a higher loss at the given probability. There are two equivalent definitions of VaR. First, it is a forecast of a given percentile, usually in the lower tail (such as 99th percentile), of the distribution of returns (or losses) on a portfolio over some period. Second, it is an estimate of the level of loss on a portfolio which is expected to be equaled or exceeded with a given, small probability (such as 1%). For example, VaR of \$1 million with a 1% probability level over one year for a bank means that the bank is expected to lose \$1 million or more over a year with a probability of 1%. VaR measure is intuitively appealing, and it does not require the assumption of normality of the distribution of returns. However, when returns are normally distributed (symmetric), VaR conveys exactly the same as the information as standard deviations (Schachter). Thus, the VaR approach can be consistent with Modern Portfolio Theory.

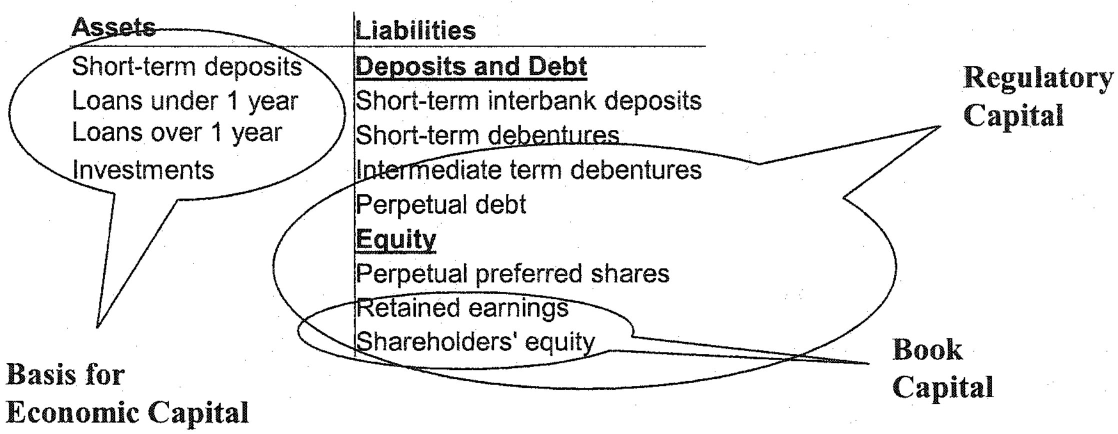
Since VaR is a measure of portfolio risk alternative to the standard deviation of returns, knowing lender's risk preferences implies that there is an optimal level of VaR for a given portfolio. The selected confidence level of VaR (the choice of the tail percentile) represents risk aversion of a lender. The optimal level of VaR for a portfolio represents the optimal level of capital to support the portfolio.

The VaR concept became very popular in the corporate finance world as a means of communicating the dollar amount of the risk of a given portfolio. VaR methods and tools are currently intensely studied by practitioners, regulators and academics because of the promise they hold for improving risk management. This study focuses on using VaR measures to estimate portfolio risk. Knowing the risks of the overall portfolio and each loan is necessary for lenders to get closer to the efficient frontier. Given the risk preferences of a lender, the optimal amount of capital to buffer against the preferred level of risk can be identified.

2.2 Economic Capital and Loan Risk 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 (see **Figure 2.2**). Book capital consists of shareholders' equity and retained earnings. Regulatory capital refers to the risk-based capital requirement under the Basel Capital Accord. It includes book capital and some forms of long-term debt. 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 level of certainty (Smithson and Hayt, July/August 2001).

Figure 2.2: Balance Sheet and Types of Capital



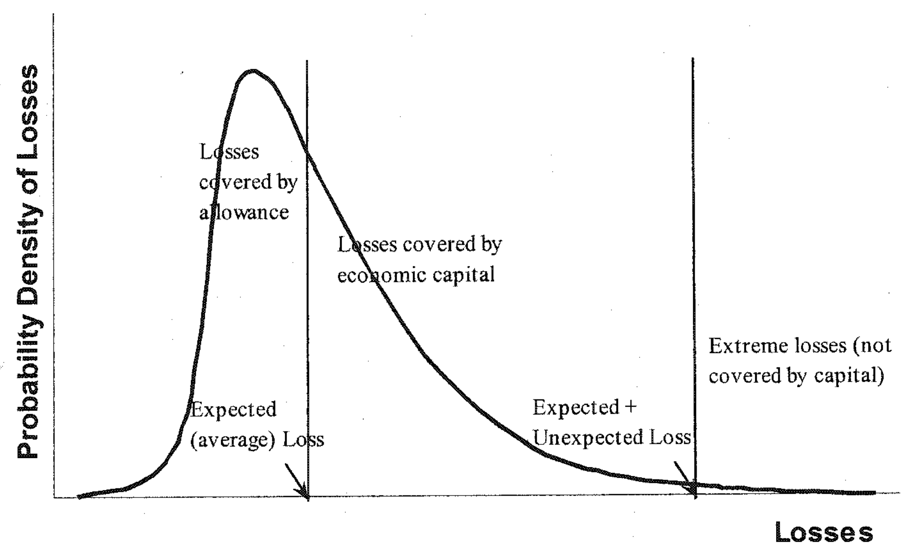
Source: Adapted from Smithson and Hayt, July/August 2001, p.67.

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. Credit and market risks are not strictly additive, even though they are assumed to be so by the Basel regulatory capital requirements (Ong, p.268). They are driven by the same market variables. Since correlation among various types of risk is not perfect, this approach is viewed as conservative resulting in the overestimation of required capital.

This study focuses on estimating the distribution of loan losses that occur due to credit risk. A loan loss distribution is pictured in **Figure 2.3**. 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.

Figure 2.3: Probability Density Function of Loan Losses



Loan returns are highly non-symmetric because there is no upside potential (Ong, p.94-95). If a borrower improves its financial condition (credit quality increases), the lender does not benefit since the borrower may refinance debt at a lower interest rate. However, if borrower's credit quality decreases, the lender is not compensated for the increased risk since the loan price remains the same. If the borrower defaults, the lender is not likely to recover legal and administrative fees involved (Ong, p. 95) and may suffer large losses.

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 2.3**. 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. $EL = PD \times LGD \times EAD$. Probability of default is the probability that a loss will occur over a given horizon. It represents loan quality. High probability of default implies low loan quality, and low probability of default implies high loan quality. Loss given default indicates the severity of default, 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 (Ong, p.123).

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 2.3**) is the difference between the amount of loss corresponding to the selected tail percentile, which represents total amount of risk finds, and the distribution mean, which represents 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% percentile (see **Figure 2.3**). 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, and correlations of default between loans. 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).[1] 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. As Ong shows, a loan portfolio that is not well diversified generally has higher losses (due to a longer and fatter tail) than the portfolio with similar characteristics but is more diversified and, therefore, needs more capital to support it.

Economic capital allocations for credit risk are based on two inputs: the target insolvency rate (100 minus the confidence level) and the estimated probability density

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[1] Ong shows (p.125) that the portfolio unexpected loss is given by $UL_P = \left[\sum_i \sum_j \rho_{ij} UL_i UL_j \right]^{\frac{1}{2}}$, where the individual unexpected losses are given by $UL_i = EAD_i \times \sqrt{PD_i \times \sigma^2_{LGD_i} + LGD_i^2 \times \sigma^2_{PD_i}}$ and ρ_{ij} is the correlation of default between loan i and loan j. Because of diversification effects, $UL_P << \sum_i UL_i$.

function for portfolio credit losses. The economic capital for credit risk is determined so that the estimated probability of unexpected credit loss exhausting economic capital is less than some target insolvency rate (Basel Committee on Banking Supervision, 1999, p.14). This is basically the definition of Value-at-Risk (VaR), which allows the estimation of required economic capital to be analogous to estimating Value-at-Risk.

The general approaches to VaR computation can be categorized into three classes: parametric approach, historical simulation, and Monte Carlo simulation. Parametric VaR approach is most closely tied to the Modern Portfolio Theory, as the VaR is expressed as a multiple of the standard deviation of the portfolio's return (Schachter). Since loss distributions are highly skewed and leptokurtic, they are usually approximated by a distribution accommodating a right fat tail such as the beta distribution. Historical simulation represents the distribution of portfolio returns as a bar chart or histogram of hypothetical returns. Each hypothetical return is calculated as that which would be earned on today's portfolio if a day in the history of market rates were to repeat itself. The assumption is that the realizations of the changes in prices and rates in the past period will remain the same in the forecasted horizon. From this histogram, the specified tail percentile is read as VaR. The Monte Carlo approach also expresses returns as a histogram of hypothetical returns. In this case the hypothetical returns are obtained by choosing at random from a given distribution of price and rate changes that are estimated using historical data. The Monte Carlo approach generates a set of portfolio revaluations corresponding to the set of possible realization of rates. VaR is read from this distribution. Each of the approaches to evaluate VaR has strengths and weaknesses, and analytical techniques can often be combined with Monte Carlo simulations to estimate the tail of a loss distribution (Schachter).

Economic capital allocations can be used to measure risk-adjusted profitability. Traditionally, rate of return on assets (ROA) and rate of return on equity (ROE) have been used to measure performance. ROA is the ratio of net income to loan volume, and ROE is the ratio of net income to lender's equity. These measures completely ignore the risk of the lending activity and the cost of capital. Risk-adjusted profitability can be measured by adjusting traditional cost-accounting measures of net income to reflect the opportunity cost of economic capital allocation. One can compare risk-adjusted profits for various activities. Risk-adjusted profitability measures are considered by risk managers "to be the pinnacle of risk/return measurement and to represent the ultimate achievement for enterprise-wide risk management" (Ong, p. 216), since they allow one to assess the trade-off between risk and return, establish consistent performance measurement across different types of loans, subportfolios, and portfolios, and allow one to price loans on a risk-adjusted basis (Ong, p. 240-241).

Virtually all financial institutions have adopted risk-adjusted return on capital (RAROC) to evaluate their performance. RAROC is similar to the Sharpe ratio[2] used to analyze performance of risky assets. It is a ratio of net income to economic capital at risk (VaR) over a specified period. RAROC of a loan can be compared to some hurdle rate reflecting the lender's cost of funds to determine if the lender's capital should be allocated to this loan. RAROC can be used to price the loan so that its return is greater

[2] Sharpe ratio is the expected return per unit of risk associated with the return. It is calculated by subtracting the risk free rate from the rate of return for a portfolio and dividing it by the standard deviation of the portfolio returns. See Sharpe for more details.

than the minimum rate of return on allocated capital. The RAROC indicator accounts for a loan's risk contribution to the portfolio, and thus provides effective capital allocation. Alternative risk-adjusted performance measures include return on risk-adjusted capital (RORAC), the ratio of net income to the Basel risk-based capital requirement, and risk-adjusted return on risk-adjusted capital (RARORAC), the ratio of economic profit to economic capital.

The RAROC is the most popular risk-adjusted measure of performance because of its focus on shareholder value. RAROC can be used to determine economic profit, or economic value added (EVA). EVA is the performance measure most directly linked to the creation of shareholder wealth over time (see Stewart for more details). EVA is the net profit minus the opportunity cost of economic capital. EVA requires a loan to be made only if it adds to the economic value from the shareholders' perspective.

2.3 Basel Capital Accord

This section covers the original Basel Capital Accord and the New Basel Capital Accord, which matches the principles and practices of economic capital. The section further describes the state of compliance with the original Basel Capital Accord in the Farm Credit System. Then it presents the plans to transition to the New Basel Capital Accord and the difficulties in the process.

2.3.1 1988 Basel Capital Accord

The Basel Committee on Banking Supervision was established by the central-bank Governors of the Group of Ten countries at the end of 1974. It meets four times a year in Basel, Switzerland. The Committee formulates broad supervisory standards and guidelines and recommends statements of best practice in the expectation that individual authorities will take steps to implement them through detailed arrangements that are best suited to their own national systems. One important objective of the Committee's work has been to increase stability of the international financial system by strengthening capital requirements for large, internationally active banks. In 1988, the Committee introduced a capital measurement system commonly referred to as the Basel Capital Accord. This system provides for the implementation of a credit risk measurement framework with a minimum permanent capital ratio of 8% by the end of 1992. The numerator of the ratio is the regulatory capital. The denominator is the total risk weighted assets. Assets such as cash and U.S. government securities are assigned zero weight, assets such as cash items in the process of collection receive 20% weight, assets such as state and local revenue bonds receive 50% weight, and all other loans and higher risk securities receive 100% weight. Off-balance sheet items are converted into credit equivalents and assigned into one of the four risk categories. Since 1988, this framework has been progressively introduced not only in member countries but also in virtually all other countries with active international banks.

The Farm Credit Administration has adopted the general features of the 1988 Basel Capital Accord such as a minimum ratio of permanent capital to risk-weighted assets. The Agricultural Credit Act of 1987 requires a permanent capital minimum standard of 7% of risk-adjusted assets (U.S. Congress, House). Farm Credit Administration (FCA) regulation 12 CFR 615.5210 states the rules for calculating the ratio. The institution's asset base and permanent capital must be calculated using average daily balances for the last 3 months. The risk-weighted assets (RWA) are the sum of all balance sheet and off-balance sheet items multiplied by the following conversion factors:

> 0%: Cash on hand, claims on Federal Reserve Banks, goodwill, claims guaranteed by the US Government agencies, unused commitments with maturity under 14 months.
>
> 20%: Loans collateralized by US agencies, claims on domestic banks, and cash items in the process of collection.
>
> 50%: Rural housing loans secured by mortgages, investment securities with maturities under 1 year, unused commitments exceeding 14 months.
>
> 100%: All other claims to private obligors, all other assets including fixed assets, leases, and receivables, direct credit substitutes including standby letters of credit, contractual obligations to purchase assets.

The 1988 Basel Capital Accord had a number of shortcomings. The regulatory risk weights ignored critical differences in credit risk among different borrowers within each risk group. So, all private sector loans were subjected to the 100% risk weight. The weights did not take into account the quality of internal risk management systems. The 8% minimum capital reserve was deemed excessive for some banks that could have effective capital reserves and could stay below the requirements. The new Basel Accord addressed these issues by reducing the gap between regulatory requirements for capital and modern capital allocation techniques.

2.3.2 New Basel Capital Accord

The Basel Committee on Banking Supervision (2001) 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. Currently the New Capital Accord is being revised based on the feedback from the industry, with revisions to be completed by the end of 2003.

The proposed capital framework of the new Accord consists of three pillars: minimum capital requirements, which seek to refine the standardized rules set forth in the 1988 Accord; supervisory review of an institution's internal assessment process and capital adequacy; and effective use of disclosure to strengthen market discipline as a complement to supervisory efforts (Basel Committee on Banking Supervision, 2001). The New Basel Accord overcame the disadvantages of the previous Basel Accord by offering institutions an opportunity to optimize capital reserve and, thus, increase profitability.

Under the first pillar, the minimum capital requirements, 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, a bank develops its own estimates of PD, LGD, and EAD. U.S. supervisors, in particular, strongly prefer that banks develop and use their own LGD and EAD data rather than standardized supervisory values since there are possible adverse incentives associated with the use of standardized supervisory values for LGD. For example, it would be undesirable to use these standardized values in the bank's internal analysis since supervisory LGD and EAD treatment is likely to be conservative and quite limited (Treacy, p.52). Internal estimates are more accurate and meaningful for an institution, since LGD is an important influence on estimated portfolio risk. Internal estimates also discourage "capital arbitrage" when a bank restructures its activities in order to satisfy standardized regulatory capital requirements but at the same time increases the risk (Carey).[3]

The IRB approach distinguishes between commercial and retail loans. Retail exposures are defined as loans to persons or small businesses, where the value of individual loans is small, and borrowers are relatively homogeneous. Corporate exposures are defined as loans to corporations, partnerships, or proprietorships when the source of repayment is based primarily on the ongoing borrower's operations. There are both foundation and advanced approaches offered for corporate exposures, but no such distinction is made for retail loans. For retail loans, a lender must divide the borrowers into various segments based on their risk characteristics, and develop either PD and LGD or expected loss function for each segment.

Under the foundation approach, the risk weight (RW) for a corporate exposure is calculated using LGD and the benchmark risk weight function (BRW) of PD according to

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[3] Two major approaches to regulatory capital arbitrage are based on the securitization of assets and the use of credit derivatives. Securitization of assets is the process of packaging loans and other illiquid assets into interest-bearing marketable securities. The regulatory guidelines place a higher risk weight on loans than on securities. To lower regulatory capital requirements, an institution can buy securitized assets instead of loans or convert some of its assets into securities. By doing this, a bank confronts other manifestations of credit risk: residual exposure to default, poor credit quality of remaining portfolio, and a possibility to provide support for the poorly performing loan pools. Similarly, credit derivatives have only 20% risk weight compared to the 100% risk weight on commercial loans. The use of credit derivatives decreases credit risk, but increases market and operational risks. For details, see Ong (p. 20-33).

the formula

$$RW = (LGD/50) \times BRW(PD) \text{ or } 12.5 \times LGD,$$

whichever is smaller (Basel Committee on Banking Supervision, 2001, §173). In this equation, $12.5 \times LGD$ is the maximum limit set to avoid a risk weight more penalizing than a deduction of the exposure from loan portfolio.

BRW is the benchmark risk weight regulatory function relating probability of default and the risk weight calibrated for an exposure with LGD = 50% according to formula:

$$BRW = 976.5 \times \Phi\,(1.118 \times \Phi^{-1}(PD)+1.288) \times (\text{Maturity adjustment})$$

where Φ is the cumulative density function of the standard normal distribution, and Φ^{-1} is the inverse. Maturity adjustment is equal to 1 for a loan with a one-year maturity and represents additional capital requirements for loans with longer maturity. The maturity adjustment under the foundation approach is based on the assumption of three-year average maturity and is equal to $(1 + 0.0470 \times (1 - PD) / PD^{0.44})$. Under the advanced approach, the risk weight RW is scaled up or down based on PD and maturity (Basel Committee for Banking Supervision, 2001, §177).

The benchmark risk weight regulatory function is the result of Gordy's paper (2001)[4], which was derived based on a simplified version of credit risk model

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[4] Let E_A be the average loss given default amount for borrower A. The systematic factor X is a standard normal random variable. Default probability of borrower A conditional on systematic factor X is given by the Vasicek formula: $P_A = \Phi\left(\frac{\Phi^{-1}(p_A) + X\,\rho_A^{1/2}}{(1-\rho_A)^{1/2}}\right)$ where ρ_A is the asset "R-squared" (asset return correlation with other loans) for borrower A, and p_A is the unconditional default probability of borrower A. The risk contribution to systematic risk (SRC) of borrower A at 99.5% confidence level is derived by setting X equal to its 99.5^{th} value of 2.576 and multiplying by the exposure:

CreditMetrics (reviewed later in Chapter 4.3.2). The regulatory function provides the VaR measure at 99.5% confidence level based on average asset return correlation coefficient of 20% and the assumption of only one systematic risk factor (such as the macroeconomic climate). With a one-factor model, it is relatively easy to set the parameters, and there is no need to use a commercial model directly. One-factor models give rise to additive capital requirements, so the resulting VaR measure does not vary in relation to portfolio composition. That's why the IRB risk weights are reasonably valid for all portfolios and do not need to be calculated with respect to any particular portfolio. (Wilde, 2001, p. 85).

The risk weight function is calibrated for a typical "granularity", which is a borrower concentration in a portfolio. The "granularity adjustment" represents the level of non-systematic risk in a portfolio. It adjusts risk weightings for diversification in credit portfolio. It is an addition or subtraction to the level of risk weighted assets, so that a portfolio with a large borrower-specific risk would require more capital, while a portfolio with low level of borrower-specific risk would require less capital than the average capital requirement. The granularity adjustment depends on Herfindahl index, PD, LGD, and sensitivity to systematic risk. The granularity adjustment was developed by Gordy (2001) based on CreditRisk+ model (reviewed in Chapter 4.3.4).

The proposed changes in the Basel Capital Accord were motivated by the improved loan portfolio management practices of large global banks. These banks began

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$\mathrm{SRC}_A = \mathrm{E}_A \Phi\left(\dfrac{\Phi^{-1}(p_A) + 2.576\,\rho_A^{1/2}}{(1-\rho_A)^{1/2}}\right)$. The Basel Committee uses average asset return correlation $\rho_A = \rho = 20\%$. Thus, $(1-\rho_A)^{-1/2} = 0.8^{-1/2} = 1.118$ and $2.576\,\rho_A^{1/2} / (1-\rho_A)^{-1/2} = 1.288$. These are the coefficients in the BRW function (Wilde, 2001).

to differentiate credit risk within their loan portfolios beyond the risk weights outlined in the 1988 Capital Accord by using the modern credit risk models in the second half of 1990s. However, the Basel Committee decided not to allow banks to use credit risk models directly (unlike market risk models) since it is nearly impossible to verify and validate them. Instead, Basel offers simplified shortcuts to calculating the amount of capital based on credit risk models that use the most conservative assumptions. Still, this is a big step forward compared to the 1988 Capital Accord. It accomplishes the objective of the Basel Committee on Banking Supervision of bringing regulatory capital more in line with economic capital.

2.3.3 Problems with Implementing the New Capital Accord

Complying with the Basel requirements will require managers to make investments into credit risk models and the process of gathering and maintaining data on credit risk. To comply with Pillar 1 capital requirements, a lending institution will need to reevaluate different internal risk rating systems, assess data availability for defaults and loss given default for each borrower grade, and risk migration of borrowers through grades over time (Basel Committee on Banking Supervision, 2001, Paragraph 284). The IRB approach focuses on the institution's risk-rating system, which requires the improvement of methodologies and data collection efforts. A bank must have 6 to 9 borrower grades for performing loans and a minimum of 2 grades for nonperforming loans. Each grade must be assigned a one-year probability of default (PD) estimate. Model outcomes and actual outcomes will need to be maintained to establish histories for model testing. Five years of PD data and seven years of LGD data is necessary to qualify for the IRB approach. Lenders will need to make investments in both technology and processes needed for acquisition and maintenance of credit data to meet standards of external verification and transparency for disclosure purposes. However, the benefit of these changes is that the data required for compliance with the Basel Accord is also required for active portfolio risk management (Haubenstock and Andrews).

Currently, the biggest hurdles to using credit risk modeling in compliance with the Basel Accord are data limitations on historical performance of loans and other modeled variables (Basel Committee on Banking Supervision, 1999). Several suggestions were made for the creation of a pooled and a shared database that will provide more reliable estimates of loan loss data such as default probabilities, loss given default and expected and unexpected losses, since not many single institutions or even groups of institutions have access to the data needed for empirical analysis (McAllister and Mingo; Farm Financial Standards Council). Any one or a group of institutions may not have enough loan losses to accurately estimate the loan loss probability distributions (Barry, 2001).

2.3.4 The New Basel Capital Accord and the Farm Credit System

The New Basel Capital Accord does not mention special treatment of agricultural loans and institutions heavily involved in financing agriculture. Loans to commercial farms and large-scale operations satisfy the Basel criteria for commercial loans. Small-scale loans to family farms fit the description of either retail loans or commercial loans. However, agricultural lending is different from commercial and retail lending. Some of the assumptions and methods used by credit risk models in commercial banking may not be appropriate for agricultural lenders.

> "Agricultural lending is characterized by the cyclical performance of farm business; lengthy, seasonal production patterns; high capital intensity especially involving farm real estate; extensive leasing of farmland; and annual versus monthly payments on intermediate and long-term loans. High incidences of financial stress and loan losses have tended to occur infrequently, but the level of losses can be high, and may be highly correlated across production units, geographic areas, and time. Government programs and payments have helped to stabilize farmers' incomes, although these programs are subject to considerable political uncertainty about their continuation, magnitude, and form. The diversity of most farm businesses generally is low, and asset ownership is largely held privately by farm families. Even a large farm is very small according to corporate small-business standards. However, larger scale, vertically coordinated production units are becoming more prevalent, especially in various types of livestock enterprises. … The traditional small-business, personalized nature of agricultural lending also favors forbearance and workout arrangements by agricultural lenders, so that risk and capital adequacy problems can arise through higher lending costs and reduced earnings from lending rather than through explicit loan losses. External credit ratings by rating agencies have not been applied to the small-scale nature of the agricultural firms, or to agricultural cooperatives, or even to financial cooperatives like the institutions of the U.S Farm Credit System." (Barry, 2001, p.115-116).

These unique features of agricultural lending require special consideration in credit risk management.

Data limitations present 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).

Currently the Farm Credit System works on determining how the New Basel Accord will be adopted within the System. Preliminary work has recently begun on redefining and expanding the risk rating system to comply with the Basel requirements, mapping existing risk ratings to the new ratings and Moody's and Standard & Poor's ratings, identifying risk weights for loans in each rating, determining loss given default ratings, and evaluating default probabilities for risk ratings (Anderson). The work is lengthy, since the feedback from Farm Credit System member associations needs to be collected and incorporated. The FCS institutions will have to incur large expenses to develop the procedures for entering the additional data, to enter the data, and to create computer systems that can handle the increased amount of data stored. The Farm Credit System plans to start the transition period for implementing the New Basel Accord in 2007, and make the transition by 2009.

2.4 Traditional Approaches to Credit Risk Modeling in Agriculture

Credit risk modeling in agriculture has been largely limited to using expert systems or risk-rating models, which evaluate credit risk of an individual borrower. Expert systems and risk-rating models have been used for a variety of purposes: credit approval, monitoring credit quality over time, credit pricing, detecting early problems, reporting, etc. In an expert system, loan quality is estimated based on the five "Cs" of credit: character (reputation of the borrower, repayment history); capital (relationship of equity and leverage); capacity (volatility of borrower's earnings); collateral (its market value); and cycle (economic conditions). Other factors and past trends in the five "Cs" criteria can be included in expert systems as well.

Risk-rating models consist of the set of borrower characteristics, such as financial and non-financial variables relating to the probability of default, and corresponding weights for each variable. A risk-rating model generates a weighted sum of scores based on a cut-off point for each borrower characteristic, placing the borrower in a certain grade that varies from minimal risk to loss. A variety of approaches (econometric techniques, neural networks, optimization models) are used to derive the set of borrower characteristics and optimum weights that place the borrower into correct risk category and, thus, create an ordinal ranking of borrowers based on probability of default. There is no uniform risk-rating model in use because of different data available to different lenders, different loan types, different approaches and data sets used to develop the models. As a consequence, the same borrower is often assigned different ratings depending on the risk-rating model used. Past research indicates wide dispersion in the use, implementation, and design of risk-rating models by agricultural lenders (Ellinger, Splett, and Barry)[5].

Developing a good risk-rating model to accurately determine borrower's creditworthiness is essential for a lending institution. The Internal Ratings Based (IRB) approach of the New Basel Capital Accord relies on internal risk-rating models for determining default probabilities of borrowers in each risk category. However, focusing on analyzing individual loans without taking into account correlation factors (i.e. assuming zero correlation) can create excessive concentrations and lead to large losses.

Risk-based capital models were recently developed in agriculture to determine capital reserve requirements of Farm Credit System Insurance Corporation (FCSIC) and Farmer Mac.

Barry, Sherrick, Lins, Dixon and Brake developed a Farm Credit System insurance risk simulation model for use by the FCS Insurance Corporation. The model treats FCS banks as borrowers and determines insurance capital reserves necessary to support their wholesale lending activities. The model evaluates each bank's capital

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[5] See Altman and Narayanan for the worldwide review of risk-rating models.

adequacy through estimating credit risk and interest rate risk using Monte Carlo simulations and VaR procedures. Correlations between banks are used to determine the overall probability of capital adequacy of the insurance fund. The small number of banks in the FCS makes the computations relatively simple.

Barry, Sherrick, Ellinger and Banner estimate loan loss rates to support a capital adequacy model for Farmer Mac based on statutorily specified stress conditions. The loss rates must reflect the highest levels of default and severity of default on Farmer Mac eligible loans that occurred during a historical period of at least two consecutive years in a contiguous area of the U.S. containing at least 5 percent of the total U.S. population. Only loan loss data from the Farm Credit Bank of Texas had sufficiently long historical series of loan-level data satisfying these conditions. The highest loss experience in Texas is used to extrapolate loss rates in other states based on the relationship between the loss rates in Texas and changes in land values. A predictive default model was then derived based on a set of factors such as solvency, repayment capacity, liquidity, loan size and changes in land value. This model is applied to individual loans in Farmer Mac's current portfolio (Barry, Sherrick, and Ellinger). The Farm Credit Administration has developed a risk-based capital test to estimate capital adequacy of Farmer Mac (see Federal Register for details). The test has three components to estimate credit, market, and operational risk capital. The test determines the amount of capital necessary for Farmer Mac to remain solvent in the next 10 years under the stress conditions specified above. The loan loss rates under stress are computed as the average loss severity rates under stress (20.9%) times loan-level default probabilities (Barry, Sherrick, and Ellinger). The loan loss rates are adjusted by year of loan life for seasoned loans. Credit risk capital is estimated as an aggregation of loan volumes adjusted by the loan loss rates under stress. Market risk capital is determined by the degree of match between the duration of Farmer Mac's assets and liabilities and the shocks of the interest rates on the market values of assets and liabilities. Operational risk capital is a 30% incremental charge to the sum of credit risk capital and market risk capital. Thus, the model produces a deterministic result yielding a specified level of capital, which is the expected loss under stress conditions. According to the risk-based capital test, Farmer Mac is adequately capitalized, having about twice as much capital as the test requires (Barry, Sherrick, and Ellinger).

The concepts of economic capital and risk-adjusted performance measurement have been applied very sparingly by agricultural lenders. Most agricultural lending institutions hold high levels of capital without estimating them based on unexpected losses. Traditionally, rate of return on assets and rate of return on equity have been used to measure performance of a lending institution, yet these measures completely ignore the risks of lending. Overall, agricultural lenders fall behind their commercial bank counterparts in credit risk measurement and modeling. Portfolio effects are largely being neglected, and credit risks are not quantified in capital allocation and performance measurement.

CHAPTER 3

APPLICATION TO AGSTAR

AgStar Financial Services, ACA (Agricultural Credit Association) assisted with the application phase of this research. AgStar provided their data, clarified rules that were used to generate the data, explained data field definitions, validated assumptions that can be used to handle missing data, and gave feedback on the results. This chapter gives some background information about AgStar Financial Services and describes how the current state of credit risk management can be improved by using credit risk models. Finally, it discusses the options that AgStar has currently available to modify its portfolio risk and composition.

3.1 AgStar Profile

AgStar is a member-owned cooperative that provides credit and credit-related services to eligible shareholders for qualified agricultural purposes. AgStar is a lending institution of the Farm Credit System (FCS), which was established by Congress to meet the credit needs of American agriculture[6]. AgriBank, a Farm Credit Bank located in St Paul, MN, provides funding to the Association. The activities of the Association are examined by the Farm Credit Administration (FCA), and certain actions taken by AgStar are subject to the prior approval of FCA and AgriBank.

After a recent merger with Farm Credit Services of Northwest Wisconsin,

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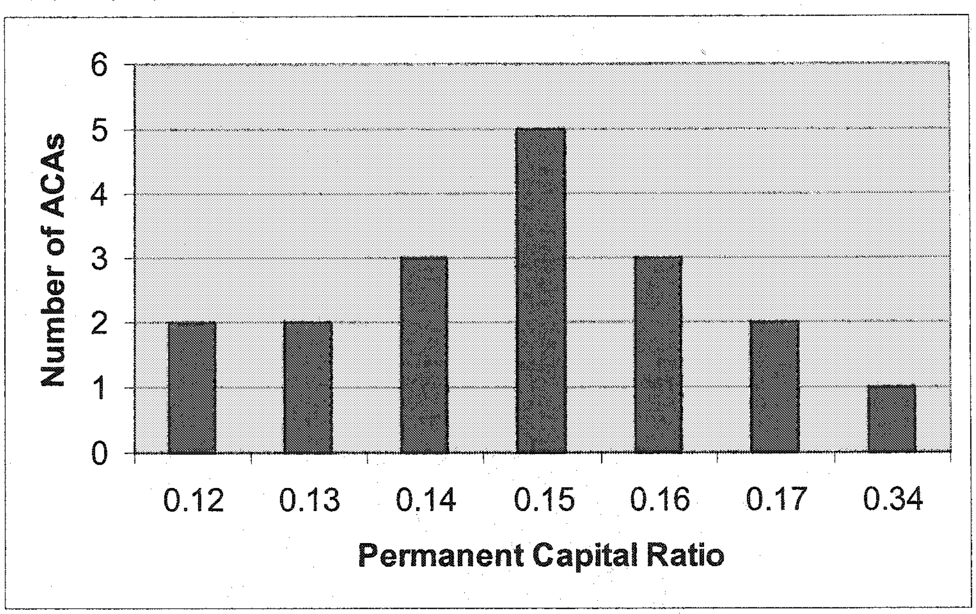
[6] The Farm Credit System is a network of borrower-owned lending institutions and related service organizations serving agricultural borrowers in all 50 states. All System banks and associations are governed by boards of directors elected by the stockholders who are farmer-borrowers of each institution. As of January 1, 2003, the FCS includes five Farm Credit Banks and one Agricultural Credit Bank that provide loan funds to 86 Agricultural Credit Associations and 13 Federal Land Credit Associations.

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 and remains one of the largest Farm Credit Associations in the nation. Eligible clients include farmers, ranchers, producers or harvesters of aquatic products, rural residents and farm-related service businesses. AgStar portfolio is dominated by loans to full-time farmers. The Association finances three primary agricultural industries: grain (mostly corn and soybean production), dairy, and swine operations. AgStar offers various risk management services and offers farm records, fee appraisals, income tax planning and preparation services, retirement planning and other consulting services for its clients. Each client, as a condition of obtaining a loan from the Association, is required to invest in the Association. There is a stock purchase requirement for obtaining a loan equal to 2% of the client's total loan amount or one thousand dollars, whichever is less. Stock purchase is also required of each client to whom a lease is issued or of each client who purchases financial services if not already a stockholder.

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%. The permanent capital ratio is the most prominent capital adequacy ratio. "Permanent capital" is defined as at-risk stock and surplus capital (retained earnings). Surplus is preferred for capital adequacy purposes, since it is more readily available, and does not undermine borrower confidence in the institution. Unallocated surplus is most preferred, since allocated surplus has been designated for a specific purpose, and would have negative consequences if impaired (Farm Credit Administration). That's why it is also important to consider the surplus ratio. AgStar's total surplus ratio (unallocated surplus divided by risk-weighted assets) was 11.6%, which is over the required minimum of 7%. The core surplus ratio (unallocated surplus less the Association's investment in AgriBank divided by risk-adjusted assets) was 9.7%, over the required minimum of 3.5% (AgStar Financial Services, 2002).

AgStar's high capital ratios are lower than those of most other Farm Credit System lenders. For example, AgriBank's permanent capital ratio was 18.9%, and permanent capital ratios among the associations in the Seventh district (FCS district served by AgriBank, which primarily includes Midwestern states) ranged from 11.8% to 34.4% and averaged 14.7% at December 31, 2002 (AgriBank, FCB and the Seventh District Associations).

Figure 3.1: Distribution of Permanent Capital Ratios Among ACAs in the 7th District as of 12/31/2002



Source: Compiled based on the data from www.fca.gov.

AgStar's permanent capital ratio of 12.1% was the lowest of all other parent agricultural credit associations (ACAs) in the Seventh District as of December 31, 2002. **Figure 3.1** shows the distribution of permanent capital ratios among the eighteen parent ACAs in the Seventh District, with most ACAs having permanent capital ratio over 15%.

AgStar has a good quality portfolio: total risk loans (restructured, nonaccrual, past due 90 days or more) are only 1.3% of total loan volume that is $2.2 billion. The Association perceived itself as overcapitalized: optimum permanent capital target on December 31, 2002, was 11.5% compared to the actual permanent capital ratio of 12.1%.

In a cooperative business organization such as a Farm Credit System association, the functions of capital are the same as for commercial institutions: 1) to provide a cushion to absorb fluctuations in net income; 2) to provide assurance to investors and public as to the institution's stability; 3) to support asset growth; 4) to contribute to the institution's earning base. Unlike in commercial lending, patrons and owners of associations are the same, which provides means for patrons to exercise control in the provided services (Farm Credit Administration).

Since AgStar is a cooperative, its goals are different from those of an investor-owned firm. The three basic principles of cooperative organization are considered to be service at cost, democratic control by members, and limited returns on equity capital (Fischer, p.16). Due to these principles, existing theoretical models treat a cooperative as a special type of firm: "The cooperative is engaged in some productive enterprise. Within the cooperative, there is presumed to be a decisionmaker. The decision-maker's problem is cast in a constrained optimization framework. Optimality is defined with reference to an assumed objective function" (Fischer, p.40). AgStar is a financial cooperative, whose objective can be viewed in EV (mean-variance) framework. A priority of an association should be the maximization of net income (Wilberding, 1997, p.3). The association's constraint is its risk-bearing ability. This constraint is limited by the regulatory requirement of a minimum permanent capital ratio. Thus, an association's objective can be defined as maximization of net interest income (as a function of economic capital and loan prices) subject to the level of income volatility (which is a function of credit risk). Credit risk management solves an association's optimization problem by maximizing net interest income through determination of the optimal level of economic capital and adequate loan pricing while keeping the portfolio credit risk within the association's risk-bearing capacity and regulatory requirements.

3.2 Current State of Credit Risk Management

Currently, AgStar uses the strategic loan portfolio management framework (SLPM), as suggested by McKinley and Barrickman. This approach was adapted for agriculture by Wilberding (1999) from AgriBank for the Seventh Farm Credit System. According to this framework, credit risk in a portfolio can be decomposed into transaction risk, intrinsic risk, and concentration risk. Transaction risk is the risk of volatility in credit quality and earnings resulting from the lender's loan selection and underwriting, loan documentation, and credit administration. Transaction risk focuses on the variability of credit quality and the volatility of earnings through individual loan transactions. Intrinsic risk is the risk inherent to a particular line of business (loan type), industry (agricultural product), and borrower's involvement in farming. Concentration risk is the aggregation of transaction and intrinsic risk within one line of business, one industry, one geographic area, or volume of loans to the largest customers (Pederson and Wilberding).

The information on transaction risk is generated by applying the internal risk-rating procedures to each loan in the portfolio. AgStar uses 8 risk classes, including four classes for acceptable loans (A1-A4), one class for special mention loans (M-5), two classes for substandard loans (S6-S7), and one class for doubtful loans (D-8). There is also a class for loans that are considered a loss (L-9). To calculate transaction risk for the portfolio, the percentage of loan volume in each risk class is multiplied by the assigned risk rating (ranging from 1 for minimal risk loans to 8 for loans of maximum risk) and by a risk weight (equal to 1 for acceptable loans and increasing to 1.5 for doubtful loans). The sum of weighted risk ratings is the weighted-average risk rating for the portfolio. It is evaluated against a rating profile for transaction risk to determine the magnitude of transaction risk (low, moderate, high) corresponding to the calculated risk rating.

Analogous to the procedure for determining transaction risk, intrinsic risk is also determined by the weighted-average risk ratings of risks in the key areas of industry type and line of business. Industry intrinsic risk score is determined as the sum of percentage of loan volumes in each industry (cash grain, dairy, swine, cattle, poultry, potatoes, and other) multiplied by the risk score of each industry (cattle and potatoes having the highest risk scores, poultry and dairy having the lowest risk scores). The line of business intrinsic risk score is equal to the sum of loan volumes in each line of business (operating, intermediate, agricultural mortgage, rural residence, leases, and other) multiplied by the risk score of each line of business (operating loans being the most risky, and rural residence loans being the least risky). Farm involvement intrinsic risk score is the sum of percentages of loan volumes in each farm involvement class (full-time, part-time, landlord, rural resident, farm related business, processing and marketing, and other) times the risk score of each farm involvement class (processing and marketing being the most risky, and rural residents being the least risky). Overall intrinsic risk for the portfolio is calculated as the average of industry, line of business, and farm involvement risk scores.

Concentration risk includes risks in four areas: largest industry, largest line of business, largest farm involvement group, and largest borrowers. To determine the concentration risk score for largest industry, the percentage of total loan volume allocated to the largest industry is divided by the percentage of this volume in bank capital. The resulting number is assigned a risk score based on a rating profile. Similar calculations are performed for concentration in line of business, farm involvement, and the largest 10 borrowers. The overall concentration risk score is a weighted average of the risk scores in four concentration areas.

The composite risk score for the portfolio is the sum of transaction, intrinsic, and concentration risk scores. The composite risk score is evaluated against a rating profile to determine if it is low ("conservative"), moderate ("managed"), or high ("aggressive").

Credit classifications serve as the foundation for determining required economic capital. Required economic capital is equal to the weighted average of loan volumes allocated to each credit classification multiplied by the percentage of economic capital allocated to each credit class. For example, these percentage capital allocations may range from 6% for best quality loans to 50% for worst quality loans. The resulting economic capital allocation percentages by risk rating are: A-1 (6%), A-2 (8%), A-3

(11%), A-4 (15%), M-5 (20%), S-6 (25%), S-7 (32%), D-8 (50%) (Pederson and Wilberding, p. 14). Analogous to the economic capital, transaction risk capital can be defined by using capital allocation percentages slightly lower than those for economic capital, since transaction risk capital covers only a part of overall credit risk.

AgStar uses economic capital as the basis for determining risk-adjusted performance indicators RORAC and economic profit. Transaction risk capital is used to calculate RORAC with transaction risk capital in the denominator.

Customer and loan data can be aggregated into various sub-portfolios based on loan type, largest agricultural industries, farm involvement types, and risk identification process. This partitioning approach can be applied to any sub-portfolio of loans.

AgStar loan portfolio management has several other components, including risk migration (a matrix of probabilities showing the likelihood of a loan migrating from its current credit risk rating to any possible future risk rating within a given time period), portfolio sensitivity (determining how shocks to factors such as farm income, expenses, government payments, nonfarm income, interest rates, and real estate value can affect portfolio credit quality), industry correlations (historical correlations between income per unit of output in major industries). These components are not used directly in the process of determining economic capital, but they provide additional information to the association credit managers.

Weighted-average risk ratings are relatively easy to compute and understand. This is an advantage of using them and, at the same time, a drawback. The weights used in the calculations of intrinsic and concentration risk, and economic and transaction capital in the existing model are subjectively defined and largely arbitrary. Associations using this model can adjust the weights to suit their perceptions of risk. This makes comparisons impossible between different associations. An individual association can change the weights over time, thus making risks and performance in various years noncomparable. Assuming the weights remain stable, the SLMP model works well for comparing changes in an association's sub-portfolio and portfolio risk performance over time. However, the SLPM model is not forward-looking, and cannot be used to predict required economic capital in the future.

The SLPM model does not consider portfolio effects in determining economic capital requirements. For example, calculating concentration risk is based on the largest industry, omitting possible correlations between the largest industry and other industries. The industry correlation component is not used in determining economic capital requirements or identifying marginal risk contribution of a new loan to the existing portfolio. Risk migration is also a separate dynamic factor. It is necessary to include information on risk migration in the analysis of economic capital requirements if one wants to make projections. Including risk migration, portfolio concentrations, and other portfolio-level effects into a model would allow for anticipating future economic capital requirements. The resulting model would be a more adequate representation of risk exposure for the purposes of planning and regulatory oversight.

3.3 Opportunities for Portfolio Management

To change the risk-return profile of its loan portfolio, AgStar has several options in the market place. It can sell loans and remove then from its balance sheets, or it can keep the loans but alter their default characteristics using credit derivatives. Credit participations and derivatives help associations to manage credit risks by separating them from customer relationships.

To change the risk of an existing loan portfolio, associations can buy and sell loans. In some cases when the customer relationship needs to be maintained, parts of the loans can be bought and sold. When a loan has two or more lenders, it is called loan participation. The originating lender makes the loan and sells part of an undivided interest in the loan to one or more other lenders. AgStar has some participations with AgriBank. For example, AgStar carries 25% of their volume, and AgriBank carries 75% of the loan volume.

Most of AgStar's participations are with commercial lending facilities. The Commercial Lending Facility (CLF) is a form of loan participation or syndication that can be created and used by associations in the Farm Credit System (Pederson and Wilberding, p.17). The CLF does not have capital of its own. Its primary purpose is to serve as a risk management tool for participating association and to provide lending opportunities within its trading territory. The CLF solves the problems of working with large borrowers that operate across the territorial boundaries of the associations and large borrowers that require more capital than a single association can provide. The CLF may have more expertise to evaluate specialized and nontraditional loans, such as loans to farm-related businesses. The CLF allows participating associations to control their large borrower concentration risk by keeping only a part of the borrower's volume. For example, a large borrower may request a loan that represents 20% of the association's total loan volume. Each association has a limit on the size of an individual loan, such as 10% of the association's total volume. Without the CLF, the association would have to decline the loan and lose the customer. The CLF allows the association to keep the customer-lender relationship and initiate the loan. Only a portion of the loan (including volume, income and expenses) will belong the association, while the other portion will belong to other associations participating in the CLF.

AgStar participates with two CLFs along with other farm credit associations: Commercial Finance Group and ProPartners Financial. The Commercial Finance Group and ProPartners Financial are governed by representatives from each participating association. Income, expenses, and losses are shared according to the association's percentage of loan volume. The share of loan volume is based on a formula that depends on the asset size of the association and program volume of the association (AgStar Financial Services, 2002, p.5-6).

Another way to change risk characteristics of the existing portfolio is through the use of credit derivatives. Credit derivatives pass the credit risk through the market while keeping the earnings component (Pederson and Wilberding, p.18). Credit derivatives are relatively new financial instruments in agricultural lending. They have not found as much use in agricultural lending as they did in commercial business lending. The Federal Agricultural Mortgage Corporation (FarmerMac)[7] has been providing associations in the Farm Credit System with credit derivatives.

One of the credit risk products FarmerMac offers is "long-term standby agreement". This agreement represents a long-term commitment to purchase qualified

[7] FarmerMac (Federal Agricultural Mortgage Corporation) is a federally chartered instrumentality of the United States which: (1) in consultation with originators, develops uniform underwriting, security appraisal, and repayment standards for qualified loans, (2) determines the eligibility of agricultural mortgage marketing facilities to contract with the Corporation for the provision of guarantees for specific mortgage pools, and (3) provides guarantees for the timely repayment of principal and interest on securities representing interests in, or obligations backed by, pools of qualified loans.

agricultural real estate mortgage loans for a fee. Thus, the risk on the loans in the pool is eliminated. Loans in the commitment pool may be removed and sold, and new loans can be added (Pederson and Wilberding, p. 19). The standby agreement reduces portfolio risks by eliminating the risk on loans in the commitment pool, which may reduce concentration risk.

Another credit risk product FarmerMac offers is a credit default swap through which lenders receive an agricultural mortgage-backed security in return for qualified agricultural real estate loans. The swap is usually in place for the life of the loans, but associations have an option to buy back the loan from FarmerMac at any time prior to maturity. Credit default swaps allow associations to swap their loans for other loans in order to decrease concentration risk or to manage large borrower exposures. For example, if an association has a lot of concentration in real estate loans, it may swap them for FarmerMac agricultural mortgage-backed security on a pool of FarmerMac guaranteed loans. This transaction allows the association to maintain the customer relationship and to eliminate default risk on these loans.

CHAPTER 4

METHODOLOGY

Broadly defined, a credit risk model includes all of the policies, procedures and practices used by a bank to estimate a credit portfolio's probability density function (PDF) (Basel Committee on Banking Supervision, 1999, p.14). The first section covers various ways of estimating default probabilities for each customer. The second section describes other components and principles of credit risk models. The third section gives an overview of major credit risk models: CreditRisk+, PortfolioManager, CreditPortfolioView, and CreditMetrics. Each of the four models is analyzed in relationship to agricultural lending to select the model best suited for modeling credit risk in agriculture.

4.1 Probabilities of Default

Probabilities of default (PD) for each client are a primary ingredient of a credit risk model. Default risk is the uncertainty regarding a borrower's ability to repay its obligations. Default can be quantified by default probability, which reflects the extent to which a borrower is likely to repay its obligations.

The diversity of methods used to estimate PD is an indicator of the fact that lenders try to improve their PD estimation techniques to achieve competitive advantage. PDs are usually estimated in one or a combination of the following three ways (Mingo):

1. PD estimates can be based on quality of loans grouped by internal risk ratings. Internal risk ratings can be "mapped" to external ratings such as Moody's or Standard & Poor's. Historical bond default data for externally rated corporate

securities are used to estimate PDs for a loan of a given rating. Alternatively, a bank can also use its own internal historical data on defaults to measure PD for a loan of a given rating. It is common for banks to use external bond dêfault data for loans of high quality because of the small number of defaults or no defaults within this group. Use of historical data for estimation of PDs for lower quality loans gives more accurate estimates because of a higher number of defaults within loans of these rankings. Bank supervisors in general prefer banks to use their own internal default data by borrower rating both for internal purposes and for the Basel IRB approach. However, mapping to rating agency default experience is still acceptable for relevant borrower types (Treacy, p.52).

Table 4.1 shows the initial mapping of Moody's and Standard & Poor's risk ratings into the current and proposed risk ratings within the Farm Credit System. Farm loans in the highest risk rating are considered to be in lower risk ratings than the top two classes for bonds. The mapping represents the judgment of the members of Farm Credit System President's Commission on Credit Risk and preliminary estimates of default rates (total default rates by loan number) in the Seventh District.

2. PD estimates can be based on statistical risk-rating models, either internally developed or externally supplied. These models are developed by applying categorical methods of data analysis (discriminant analysis, logit or probit regression) to historical data on loans of different quality (usually defaulted and nondefaulted loans). The models usually produce PD estimates as a function of financial and nonfinancial borrower characteristics.

3. PD estimates for publicly traded borrowers can be based on default probability associated with the stock price and equity value, such as KMV's CreditMonitor.

These options for estimating PDs are approved by the New Basel Accord: "Banks should consider internal default experience, mapping to external data, and statistical default models. One can be a primary source of information, and others can be used for adjustments to the initial PD estimate." (Basel Committee for Banking Supervision, §274).

Table 4.1: Preliminary Mapping of Risk Ratings and PDs for the FCS

Rating Agencies				Proposed	Seventh District				
Moody's Risk Rating	Moody's PD	S&P's Risk Rating	S&P's PD	FCS Rating	Rating	Operating PD	AgMrtgg PD	RuralRes PD	Term PD
Aaa, Aa	0.00%	AAA, AA	0.00%	1					
Aa, A	0.08%	AA-A	0.01%	2					
A	0.01%	A	0.04%	3	1	0.38%	0.35%	0.25%	0.57%
Baa1, Baa2	0.12%	BBB+, BBB	0.02%	4	2	0.67%	0.67%	0.42%	0.80%
Baa2, Baa3	0.12%	BBB, BBB-	0.26%	5	2	0.67%	0.67%	0.42%	0.80%
Ba1	0.78%	BB+		6	3	1.25%	1.10%	1.01%	1.44%
Ba2	0.65%	BB+, BB	1.12%	7	3	1.25%	1.10%	1.01%	1.44%
Ba3	2.93%	BB, BB-		8	4	5.17%	3.49%	5.29%	4.09%
Ba3, B1	7.71%	BB-, B	6.06%	9	4	5.17%	3.49%	5.29%	4.09%
	13.66%	CCC	25.22%	10	5				

Source: Anderson, slide 22.

Mapping to external bond default data is not appropriate for agricultural borrowers, which are privately owned and much smaller than corporate bond issuers, unless adjusted for the difference in borrower, loan, and collateral types. The use of statistical models relying on annual borrower's financial and nonfinancial characteristics would be problematic for associations like AgStar who keep the last six balance sheets and income statements, which are not necessarily annual statements. Thus, there may be three balance sheets for one year and none for another year. Since AgStar's risk rating function sufficiently discriminates between probabilities of default as shown later in the study, AgStar's internal historical default experience is used to estimate average probability of default for each risk rating. This is consistent with the New Basel Capital Accord that requires mean probability of default for each risk rating, not a probability of default for each borrower.

4.2 Components of Credit Risk Models

The choices of various methodologies and approaches that lenders use in their credit risk models are largely subjective. They are based on lending institutions' credit culture and characteristics of loan portfolio. The elements of credit risk models covered in this section include choice of time horizon; approaches to credit aggregation; default-mode versus mark-to-market paradigm to measuring credit loss; conditional and unconditional models; and approaches to dependence between loan defaults.

Time Horizon

Most banks adopt a one-year time horizon across all types of assets, since this is a time period over which loans are renewed; loss mitigating actions such as loan sales could be taken to eliminate the possibility of further losses; new capital could be raised to offset portfolio credit losses beyond the horizon; accounting, capital planning and internal budgeting statements are prepared (Basel Committee on Banking Supervision, 1999, p.17). In agricultural lending, many loans are repaid on an annual basis because of seasonal production patterns. This makes the assumption of a one-year time horizon very appropriate.

Default-Model versus Mark-to-Market Paradigm

Credit risk models usually follow one of the two approaches to credit loss: the default-mode (DM) paradigm or mark-to-market (MTM) paradigm. The default-mode paradigm assumes that credit loss happens only when a borrower defaults within the planning horizon. This paradigm is usually consistent with "buy and hold" lending. In this case, the derived capital requirement measure is closer to a book-value capital measure than to a full market value of economic capital measure. The default-mode definition of loss is more consistent with traditional book-value accounting that determines legal and regulatory standards of bank solvency (Gordy, 2002, p.1). The mark-to-market paradigm generalizes the default-mode paradigm by incorporating changes in credit quality. Default does not happen spontaneously. It is usually preceded by deterioration of borrower's financial position. The degradation of creditworthiness is called "credit migration". It is represented by a transition matrix. Transition probabilities indicate how borrower's creditworthiness improves or deteriorates over time. Default probability is the probability of reaching the final state – default. A credit loss is defined as the reduction of the loan's value over the planning horizon. In agricultural lending, loans are usually held to maturity; thus, the default-mode paradigm is sufficient. Since the mark-to-market paradigm is a generalization of the default-mode paradigm, it also can be used in agricultural lending. It is not required.

Top-Down versus Bottom-Up Approach

Economic capital is associated with volatility, or unexpected losses, in the economic value of a lending institution. This volatility cannot be observed directly.

Rather, it can be approximated by the volatility of earnings or of the value of individual transactions (Smithson and Hayt, July/August 2001). This volatility can be measured via a "top-down" or "bottom-up" approach. The top-down measures use overall cash flow volatility to estimate the volatility of each loan's value. Top-down measures are usually used for high-volume businesses such as consumer or small business lending, where there is little information available on individuals, each transaction's volume is small, and transactions are homogeneous. The bank can base its estimated PDF on the historical credit loss rates for each subportfolio taken as a whole. Pooled data hides details on individual loans. The limitation of top-down models is that they are not sensitive to changes in portfolio composition. If the quality of customers changes over time, PDF estimates may be misleading.

Most lenders track individual loan characteristics. This enables them to use the bottom-up approach. Bottom-up methods are usually applied to measure credit risks of middle-market and large customers where information on each borrower is available, and when changes in portfolio composition may affect the overall PDF. Bottom-up models quantify credit risk for each loan based on loan credit rating, which is tied to its probability of default. To measure credit risk for the whole portfolio, the risks of individual loans are aggregated accounting for correlations.

AgStar, like most agricultural lenders, keeps track of borrower's characteristics, enabling the use of the more comprehensive and precise bottom-up approach. Presence of large-scale corporate farms creating significant concentrations in agricultural portfolios requires the bottom-up approach for at least the subportfolio of larger borrowers. All major credit risk models (reviewed later in the chapter) use the bottom-up approach.

Conditional versus Unconditional Models

Credit risk models can be categorized into conditional and unconditional models. Unconditional models mostly rely on borrower-specific information, while conditional models also incorporate information on the state of the economy (e.g., unemployment rate, stock prices, interest rates, inflation). Currently, most credit risk models are unconditional because of insufficient data series for estimating the impact of macroeconomic factors on default probabilities and other model parameters with a reasonable precision. Some credit risk models such as KMV's PortfolioManager use different conditional approaches, for example, in estimates of asset values that are inherently forward-looking since they are based on current equity prices that reflect expectations about the future. Unconditional models are designed to use PD, rating transitions and correlations that are long-run averages of these parameters ideally over many credit cycles. However, the short-term outlook may be dependent on the state of the economy. Nickell, Perraudin and Varotto find that business cycle peaks and troughs make a difference in default probabilities of low-grade bond issuers.

Conditional models also have drawbacks. Since it is impossible to predict the state of the economy, conditional models may have limited value in predicting future losses. Parameter estimates may be subject to considerable uncertainty since estimation of credit cycle effects is a very complex process (Basel Committee on Banking Supervision, 1999, p.29). Also, considering the same factors more than once should be avoided in conditional models. For example, macroeconomic factors could have already been considered in the rating process, when a borrower has been assigned a specific risk category (Kurth, Taylor, and Wagner, p. 242). Macroeconomic factors affect borrower's solvency, liquidity, profitability, collateral position, and repayment capacity, which in turn determine borrower's risk rating.

Agricultural lending is characterized by cyclical performance of farms due to macroeconomic variables (commodity prices, level of government support, interest rates) that have significant effects on borrower creditworthiness. Shepard and Collins find a strong link between failures in agricultural and nonagricultural sectors suggesting that federal macroeconomic policies may heavily influence success of farms. Pederson and Wilberding (p.2-4) discuss how various macroeconomic shocks affect economic conditions and credit risk in agriculture. The absence of historical data on borrowers and loan performance covering the whole credit cycle (at least 10 years long) makes the evaluation of the effect of macroeconomic variables on agricultural borrowers very difficult. There is also a question of applicability of past data to forecast farm creditworthiness in the future. The effect of macroeconomic variables on farms is likely to be different when structural change occurs. Agriculture is currently going through changes such as expanded use of biotechnology, which may lead to overproduction and declining commodity prices, the transition to larger corporate style farms, increased use of hedging and insurance, and changes in the use of contracts in agriculture. The inability to predict the effect of future macroeconomic changes on default probabilities and the lack of historical data makes the application of conditional approach to agriculture questionable at this point in time. As more data becomes available over time and the effects of the current structural changes are known, it would be desirable to condition default probabilities and other model parameters to account for macroeconomic factors.

Correlation Effects

The most challenging aspect of the credit risk modeling process is accounting for correlation factors. These factors affect PD, LGD, risk migrations, and changes in credit spreads for mark-to-market models. In general, this process is difficult and imprecise. It involves many simplifying assumptions since correlations among random variables are hard to estimate with short historical series (Federal Reserve System Task Force on Internal Credit Risk Models, p. 25-26). Because of these data limitations, correlations between different types of risk factors (between rating migrations and LGDs, between rating migrations and exposures, and between LGDs and exposures) are typically assumed to equal zero. Virtually all credit risk models consider only correlations between defaults of different borrowers.

Credit risk models account for correlations between borrower defaults in two different ways; using structural approach or using the reduced-form approach. Under the structural approach (used by CreditMetrics and PortfolioManager), the random variable called a migration risk factor (unobservable latent variable) determines the change in the borrower's risk rating, including default. Migration risk factors are often interpreted as being represented by a borrower's asset or equity values. The correlations among borrowers' defaults are derived based on correlations between migration risk factors, which are estimated using historical data such as risk migrations for corporate bonds.

Under the reduced-form approach (used by CreditRisk+ and CreditPortfolioView), models assume a particular functional relationship between customers' expected default rate or migration matrix and background factors, which can be either observable variables (such as macroeconomic indicators) or unobservable random variables. These background factors give rise to correlations among borrowers' default rates and risk migrations (Basel Committee on Banking Supervision, 1999, p. 26-33).

Agricultural lending is characterized by high correlations across production lines and geographic areas, so it is important to account for correlations between borrower probabilities of default. Both the structural and reduced-form approaches seem to be appropriate as long as they do not rely on data from incompatible sources (such as data on corporate bonds) and as long as the model uses correlations based on historical agricultural data.

4.3 Major Credit Risk Models

Table 4.2: 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 Probabilities
Data needs	Asset values, asset value volatilities	Credit spreads, yields for risk ratings, asset value volatilities	Economic factors driving default probabilities, borrower sensitivities to economic factors	Default probabilities, volatilities of default probabilities
Correlation of credit events	Multivariate normal asset returns	Multivariate normal asset returns	Factor loadings	Correlation with expected default probability

In the financial world, the four most prominent 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 4.2** shows the brief comparison of the models.

4.3.1 KMV Portfolio Manager

KMV Portfolio Manager uses the option pricing theory in valuation of loans, as first suggested by Merton. There is an assumption that borrowers have an incentive to repay the loan if firm's assets exceed the amount borrowed, and default on the loan otherwise[8]. According to Merton's theory, if a loan is repaid, the lender will earn a fixed return on the loan. If a loan is in default, lender can suffer large losses that may exceed the outstanding principal and interest. This behavior makes the loan payoff to the lender analogous to writing a put option on the assets of the borrowing firm. The value of a risky loan is dependent on the variables used in calculating the value of the option: the short-term risk-free interest rate, the loan time horizon, the amount borrowed, the market value of assets of a firm, and the volatility of asset value. The last two variables are usually not directly observable. KMV solves this problem for corporate borrowers by using firm's stock price to estimate market value of its assets, and volatility of firm's equity to estimate volatility of assets. KMV offers a "Private Firm Model" for nontraded firms and approximates their asset value and asset volatility by those of publicly-traded

[8] This assumption holds for agricultural borrowers as well. Babetskaya shows that debt-to-asset ratio is the major consistent predictor of borrower's repayment capacity.

firms with similar characteristics. It would not be appropriate for agricultural lenders to use the Private Firm Model since there are no publicly traded firms with similar characteristics: agricultural firms are in general a lot smaller than even smallest of publicly-traded firms.

One approach would be to directly compute the borrower's market value of assets based on balance sheet information, and calculate volatility of assets based on historical data. However, AgStar cannot insure that a borrower's balance sheet valuation of assets is truly a market value. It is hard to estimate market value of farm real estate and machinery, which are the biggest part of farm assets. Initial book values of assets are adjusted every year based on appreciation and depreciation, but the estimates are likely to differ from true market values.

After all of the five required variables are available, KMV can generate the probability of default function for the borrower. Distance from default is calculated as the difference between asset value and loan value, divided by the volatility of asset value. If one makes an assumption that future asset values are normally distributed around the firm's current asset value (projected growth rate can be incorporated in calculating the future asset value distribution), probability of default can be derived from the distance to default using a normal distribution. However, instead of using the questionable assumption of normally distributed future asset values, KMV generates an empirical PD by maintaining a large worldwide historical database of firm default data. The KMV model calculates PD as the number of firms that defaulted within a specified time horizon with asset values of given distance from default divided by total number of firms with asset values of given distance from default. Empirically based PD can vary significantly from PD based on the normal distribution. It is doubtful that corporate default data in the database is comparable to defaults of agricultural producers. The questionable assumption of normally distributed asset values can be used as the alternative if the model is applied to agriculture.

In estimating correlations between loan defaults by asset value correlations, relationships between borrowers' asset values are divided into a set of common and specific factors. Each firm has a unique R-squared representing the amount of asset volatility explained by systematic economic factors. Loan value correlations are determined as a function of PD, and the underlying asset correlation is approximated by stock returns for publicly-traded companies. The problem with this approach for agricultural lenders is the requirement to use the borrower's asset values as market values of assets. Correlations between adjusted book values of assets would not be an accurate representation of correlations in market values. An alternative would be to make an assumption that market values of assets are closely related to industry (hogs, soybeans, corn) returns and approximate correlations between asset values by the correlations between industry returns. Market values can be related to industry returns by the present value model that calculates current market value of an asset as a total discounted cash flow from the asset.

KMV model is of doubtful applicability for agricultural lenders since a number of strong assumptions would need to be made. These assumptions include: approximating market asset values by adjusted book values, assuming normal asset returns, and approximating asset value correlations by industry returns.

4.3.2 J.P. Morgan's CreditMetrics

J.P. Morgan's CreditMetrics model for credit events is an ordered probit model. There are multiple states of borrower ratings, and the borrower state is determined by the location of unobservable latent random variable in relation to the cut-off values for the states. Like KMV Portfolio Manager, CreditMetrics is a mark-to-market model that captures not only defaults but also the migrations across nondefault states. CreditMetrics uses the VaR framework to determine value and risk of nontradable assets such as loans. Since loans are not publicly traded, neither the loan's market value nor the volatility of the loan value over the time horizon are required to calculate VaR. These variables are estimated based on data on the borrower's risk rating, the risk rating transition matrix, recovery rates on defaulted loans, and credit spreads and yields in the loan market. Risk rating migrations can be based on historical data on publicly traded bonds or loans collected by Standard and Poor's, Moody's, KMV, or other analysts. Risk rating migration could be estimated using the historical data on changes in loan ratings. The value of a loan under different risk ratings is calculated as a total discounted cash flow from the loan based on risk-free rates, the contractual loan rate, the loan amount, and credit spreads for loans of particular risk-rating classes. Credit spreads (defined here as the difference between the risk-free interest rate and the interest rate for borrowers of a given risk rating) are derived from observed spreads in the corporate bond market over Treasury bonds. Credit spreads could be estimated based on historical loan data. However, there would be a problem estimating credit spreads for lower quality loans, since loans are generally written for acceptable risk borrowers. If borrower risk classification deteriorates after a loan is initiated, credit spread is not affected if the interest rate for the loan is fixed until maturity date.

CreditMetrics calculates VaR either by assuming a normal distribution of loan values or by using the actual distribution of loan values. To calculate VaR, the expected loan value at the end of the time horizon is calculated as the sum of each possible loan value times its transition probability over the time horizon. Assuming a normal distribution, volatility of loan value can be found from the distribution of loan values, and VaR is calculated based on the standard deviation and normal distribution parameters. This VaR will likely underestimate true value, since the actual loan distribution has a long left tail. VaR estimates based on actual distributions can be derived from the distribution of loan values using linear interpolation for desired significance levels of VaR. The resulting VaR measures can be directly compared to the Basel capital requirement of 8%.

The CreditMetrics approach to calculating correlations is similar to the KMV methodology. CreditMetrics uses correlation between equity returns to estimate asset correlations between two firms. The individual borrowers are grouped by country and industry, and industry indexes are used to construct a matrix of correlations between industries. CreditMetrics provides users with a spreadsheet of industry returns and correlations derived from equity price data. Private firms are assumed to have the same correlations as publicly traded firms with similar industry and country characteristics. The correlation data that CreditMetrics provides in its database cannot be used in this study because all agricultural companies are treated as belonging to the same industry. Also, CreditMetrics includes only publicly-traded companies. That is not comparable to small farm businesses. As in the case with KMV Portfolio Manager, an assumption that asset correlations are approximated by the correlations of industry returns can be made. Alternatively, uniform constant correlations can be used, as CreditMetrics recommends instead of ignoring correlations in the absence of suitable data. This would not be appropriate since the traditional agricultural and general economy sectors are independent of each other, as this study shows later in Section 6.5.

CreditMetrics data requirements are hard to satisfy in the case of agriculture since the data on credit spreads for low quality loans is not available in the historical database, while market data on spreads for corporate bonds is not relevant. Besides, approximating asset value correlations by correlations of industry returns or adjusted book values of assets, or using uniform constant correlations would not be very accurate.

4.3.3 McKinsey's CreditPortfolioView

McKinsey's CreditPortfolioView is a multi-factor model that simulates the joint conditional distribution of default and migration probabilities for various rating groups in different industries and countries conditional on macroeconomic factors. It analyzes portfolio risk and return using econometric techniques and Monte Carlo simulation. The rating transition matrices are related to the state of the economy, giving increased likelihood of an upgrade and decreased likelihood of a downgrade during an upswing of a credit cycle. It is the contrary when the economy becomes weaker. Following the notation of Koyluoglu and Hickman, let i be a borrower of a specific country, industry, and credit rating, t is the time period, and k is a macroeconomic factor. Each borrower's default probability $p_{i,t}$ depends on a normally distributed "index" of macroeconomic factors for the borrower. The macroeconomic index $y_{i,t}$ is represented in a multi-factor model as a weighted sum of macroeconomic variables, $x_{k,t}$ (GDP, aggregate savings rate, government expenditures, unemployment, etc.) that depend on normally distributed random shocks and their past histories:

$$x_{k,t} = a_{k,0} + a_{k,1}\ x_{k,t-1} + a_{k,2}\ x_{k,t-2} + \ldots + \varepsilon_{k,t} \text{ and}$$

$$y_{i,t} = b_{i,0} + b_{i,1}\ x_{1,t} + b_{i,2}\ x_{2,t} + \ldots + \nu_{i,t}$$

where $\varepsilon_{k,t}$ and $\nu_{i,t}$ are normally distributed random variables. The index is transformed to a default probability using the Logit function:

$$p_{i,t} = 1/(1+e^{Y_{i,t}})$$

Factor loadings $b_{i,k}$ for the index are determined with the help of logistic regression from the empirical relationship between sub-portfolio default probabilities (for different country/industry/credit rating) and explanatory macroeconomic variables. The $a_{k,j}$ coefficients for the macroeconomic variables are determined through one of several econometric models suggested by Wilson.

Portfolio loss distributions are calculated using Monte Carlo. Random variables $\varepsilon_{k,t}$ and $\nu_{i,t}$ for each macroeconomic variable and index value are drawn. Macroeconomic variables and index values are calculated based on their past values and the random variables. Then default probabilities are calculated from the macroeconomic index. The distribution of default outcomes is calculated by successively convoluting each borrower's two-state distribution of outcomes. This procedure is repeated thousands of times to create a distribution of portfolio losses (Koyluoglu and Hickman, p.2).

Only the state of the economy (macroeconomic variables), country, industry, and rating need to be specified for publicly-traded borrowers to estimate probability of default from McKinsey's database. This database has information on industry sensitivities to macroeconomic factors $b_{i,k}$ for each major country/industry/credit rating. Probability of default for each subportfolio (conditioned on the state of the economy) is estimated based on borrower sensitivity to the state of economy and rating. Default losses are projected on the basis of marginal default probabilities over time discounted to the present. Default correlations between borrowers are determined by the systematic risk driving average default probabilities. They are derived from the joint probability of default in each state of the economy. The output of the simulation is a plot of portfolio loss (or gain) against the probability.

The CreditPortfolioView approach can be used along with CreditMetrics to calculate VaR for any number of years into the future by replacing the unconditional transition matrix with a different transition matrix for each year into the future, conditional on the business cycle. Thus, this approach can be considered complementary to CreditMetrics. It overcomes the bias of stationary transition probabilities (Saunders, p.66).

McKinsey's approach would be hard to implement in agriculture, since there are no data series of sufficient length for the estimation of sensitivities of borrowers of various credit ratings in different agricultural industries to underlying macroeconomic variables. Historical data for other industries is not applicable since economic cycles in agriculture are different from the cycles in other industries that are correlated with the general economy. Also, recent changes in agriculture may affect industries' sensitivities to the state of economy in unpredictable ways, so historical data is of questionable relevance.

4.3.4 Credit Suisse Financial Products' CreditRisk+

Credit Suisse Financial Products' (CSFP) model CreditRisk+[9] is based on the insurance approach that uses mortality analysis to model a sudden event of borrower default. Only default risk is modeled, not downgrade risk[10]. 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. Each individual loan is assumed to have a small probability of default. The occurrence of default is represented by a Poisson distribution. CreditRisk+ ties loan default probabilities to the mean default probability of the "sector" of interest, which varies according to a gamma distribution. The rates of severity of default are also uncertain. To make the process of estimating loss severity on individual loans easier, loan loss severities are rounded and banded into discrete categories. The frequency of defaults and the severity of losses produce a distribution of losses for each band. Aggregating losses across bands produces a discrete loss distribution for the loan portfolio.

Default correlations in CreditRisk+ model are caused by background factors represented by sectors, such as industries or geographic regions. Different sectors are affected to different degrees by the state of the economy. Within each sector, borrowers are presumed to respond to the same systematic risk factors. Background factors affect

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[9] 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.

[10] Broeker and Rolfes show how to incorporate the effect of rating migrations in CreditRisk+ framework.

the default probabilities of borrowers who belong to the sector. Thus, they may cause defaults of borrowers in the same sector to be correlated, even though there is no causal link between them. Instead of explicitly deriving default correlations, concentration effects are derived through the use of means and volatilities of default probabilities for each sector[11].

Because the risk of default is assumed to fit a certain distribution, it is possible to calculate the distribution of portfolio losses analytically. Thus, compared to the other models, the CreditRisk+ approach is, in some ways, "closest to the original mean/ variance approach of Markowitz, which assumes normally distributed asset returns and yields closed form results for portfolio risk and security risk" (Smithson and Hayt, March 2001, p.36).

The CSFP model requires relatively few data inputs: credit exposures, recovery rates, borrower default probabilities and volatilities of default probabilities for various credit ratings and sectors. All of these inputs could be estimated from AgStar's historical data. Unfortunately, estimation of volatilities of default probabilities will not be precise, since five years of data do not cover the whole credit cycle, but this problem will be solved as longer series of data become available. CSFP recommends using standard deviations of default probabilities around 70-100% of the means of default probabilities[12], so lenders can use estimates based on historical data as well as CSFP's

[11] Default rates in each sector are assumed to have the Gamma distribution, which is a skewed distribution determined by two parameters, mean and the scale parameter. The Gamma distribution approximates the Normal distribution when its mean is large.

[12] This range for volatilities of default probabilities is based on historical default experience of U.S. corporations. It is the same based on AgStar's data as shown later in the study. The study by Barry, Sherrick, Ellinger, and Banner produces the standard deviation of the default probability equal to the mean of default probability.

recommendations. Correlations between default events can be highly dependent on the underlying time period. An advantage of CSFP's approach to accounting for default correlation is that it is easier to perform scenario analysis on the volatilities of default probabilities than on explicitly derived correlations (CSFP, p.15).

The CreditRisk+ approach is valid for any portfolio where the default probability for each borrower is small. This assumption is true for AgStar, whose default probabilities vary from 0.25% for the highest risk rating to 25% for the lowest risk rating, averaging 1.22%, as reported in Chapter 6. This default experience is comparable with that of other agricultural lenders.

This model seems to be appropriate for modeling credit risk in agriculture. Its data requirements are satisfied by historical data available in most record-keeping systems of agricultural lenders, and its assumptions are met reasonably well.

4.3.5 Model Selection

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). Parameter inconsistency results from using totally different data sets to estimate parameters. Since the models produce different results when input parameters are inconsistent, Koyluoglu, Bangia, and Garside suggest that the quality of estimates from different models should be compared to find out which model uses the most appropriate data. For example, Merton-based asset correlations (Merton) derived from equity price relationships can be most accurate for publicly-traded companies, while volatilities of default probabilities derived from historical experience may be more appropriate for consumer loan portfolios. Model outputs are most sensitive to PDs, LGDs and default correlations. It is important that model inputs be unbiased estimates of their true values. (Basel Committee on Banking Supervision, 1999, p. 35). Model mis-specification may be another source of difference of results from various models. For example, the assumption of normally distributed asset returns in a KMV-type model may not be appropriate for agricultural borrowers.

Which approach performs better is an empirical issue under specific circumstances. Koyluoglu and Hickman conclude that the four models described above are so closely related that users need to select a model not based on "theoretical correctness" but on practical concerns such as ease of use and data availability. Lentino and Pizada also conclude that selection of the model is secondary to providing consistent and reliable data for a model. Since credit risk measurement usually depends more on the quality of inputs rather than on the modeling approach, a model must be selected based on the use of a more reliable set of parameters.

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).

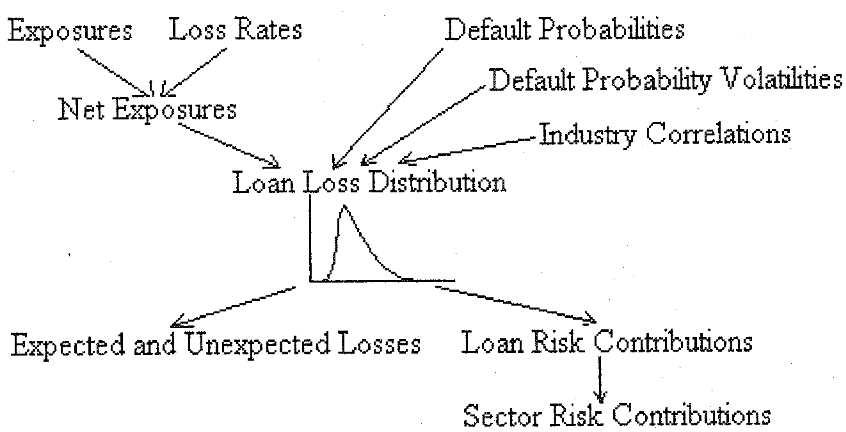
CHAPTER 5

MODEL DEVELOPMENT

This chapter first gives an overview of the CreditRisk+ model. Then it describes how disadvantages of the original model can be overcome by incorporating the latest research: using an alternative faster and more accurate algorithm, and accounting for default correlations between industries. Finally, the chapter describes how the model is implemented.

5.1 Overview of CreditRisk+

Figure 5.1: Model Structure



As **Figure 5.1** shows a brief overview of the model structure. The model inputs are exposures, default probabilities and their volatilities, and correlations of default between sectors (defined as industries in this study). In the event of default, a lender suffers a loss of a known size, which is the lender's net exposure on a loan. Net exposure v_i for each loan i is equal to the loan volume times the percentage loss given default. It is the loss after recovery. All losses and exposures are multiples of a standardized loss unit (see CSFP, Appendix A3 for details). Default probability p_i for each exposure i is equal to the customer's default probability determined by the customer's risk rating. Standard deviation of default probability σ_k for each sector k, $k = 1, \ldots, K$ is equal to the sum of standard deviations for all loans in the sector, $\sigma_k = \sum_i \sigma_i$ for $i \in k$. Volatility of default probability σ_i for each loan i is equal to the borrower's volatility of default probability as determined by his/her risk rating. This method of estimating sector default volatilities assumes that the borrower's credit quality within a sector is a more significant influence on the volatility of default than the background factor affecting the sector[13]. Alternatively, volatilities of default probabilities per sector could also be estimated directly "if the nature of the sector made it more appropriate" (CSFP, p. 44). Correlations between sectors are not an input in the original model assuming independence of defaults in various sectors, but it is an input required later in the development of the model.

Following the notation by Gordy (2000), loan defaults are assumed to be caused by a vector of K "risk factors" $x = (x_1, \ldots, x_K)$ corresponding to sectors. Each sector (later defined as industry such as dairy, crops, swine, etc.) represents a unique risk factor. Default probabilities in each sector are correlated due to the impact of the common risk factor. Conditional on the risk factors x, defaults of individual loans are assumed to be identically and independently distributed Bernoulli variables[14]. The conditional probability $p_i(x)$ of default for loan i is determined by its unconditional probability p_i (corresponding to the risk rating of its borrower), the realization of risk factors x, and the vector of sector weights $(w_{i1}, \ldots, w_{iK})$ which measure the sensitivity of loan i to each of the

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[13] This assumptions holds for AgStar's data. Default probabilities by risk rating in **Table 6.2** show a lot more variability than default probabilities by industry in **Table 6.3**.

[14] A Bernoulli random variable takes the value of either 0 (in this case, corresponding to the event of a loan not defaulting) or 1 (corresponding to the event of a loan default). The distribution of a Bernoulli variable X is completely defined by the probability of the event $X = 1$ (loan default).

risk factors. For example, if a loan is assumed to be fully assigned to sector k, then w_{ik} = 1 and others $w_i = 0$. The sector weights w_{ik} sum up to one for each loan. The probability function conditional on the risk factors x is specified in CreditRisk+ as

$$p_i(x) = p_i\left(\sum_{k=1}^{K} \frac{x_k}{\mu_k} w_{ik}\right) \tag{2}$$

where p_i is the unconditional default probability for loan i, and the x_k are positive-valued with mean μ_k. The risk factors x serve to scale up or scale down the unconditional p_i. A high draw of x_k (over μ_k) increases the probability of default for each loan in proportion to the loan's weight w_{ik} on that risk factor; a low draw of x_k (under μ_k) scales down all default probabilities. (Gordy, 2000).

The model's major output is the loan loss distribution: its mean ε, standard deviation σ, and tail percentiles. Mean and standard deviation can be calculated analytically. Expected loss ε_i for each loan i is the product of net exposure ν_i (loss after recovery) and unconditional default probability p_i, $\varepsilon_i = \nu_i \cdot p_i$. Expected loss for each sector is the sum of expected losses for all loans in the sector, $\varepsilon_k = \sum_i \varepsilon_i w_i$ for $i \in k$. Portfolio expected loss (distribution mean) is the sum of expected losses for all loans or all sectors, $\varepsilon = \sum_{k=1}^{K} \varepsilon_k = \sum_i \varepsilon_i$ for all i.

The total expected number of defaults μ is the sum of the expected number of defaults in each sector μ_k, $\mu = \sum_{k=1}^{K} \mu_k = \sum_{k=1}^{K} (\sum_{i \in k} w_{ik} p_i)$.

Total risk in a portfolio can be represented as the sum of two risks, systematic and non-systematic. Systematic risk is due to correlated defaults in a portfolio caused by the same economic forces (risk factors). Non-systematic risk is borrower-specific risk. It is very small in large and homogenous portfolios. Non-systematic risk is significant when there are large single exposures or only a few exposures in a portfolio. Variance of losses in a portfolio is the sum of variances due to systematic risk and non-systematic risk. It is derived in CSFP, Appendix A13.2, and is given as

$$\sigma^2 = \sum_{k=1}^{n} \varepsilon_k^2 \left(\frac{\sigma_k}{\mu_k}\right)^2 + \sum_i \varepsilon_i v_i. \tag{1}$$

The next two pages follow the overview of CreditRisk+ model by Gordy, 2000. Instead of calculating the distribution of defaults directly, CreditRisk+ uses the probability generating function (PGF) for defaults, which is a compact way of representing discrete probability distributions[15]. If k is a discrete random variable representing the number of defaults, its PGF $F_k(z)$ is a function of an auxiliary variable z such that the probability of the number of defaults k being equal to n is given by the coefficient on z^n in the power series expansion of $F_k(z)$, $F_k(z) = \sum_{n=0}^{\infty} p(n \text{ defaults})\, z^n$. The PGF has some useful properties:

- The PGF of a sum of independent random variables is the product of their PGFs.
- The moments of the probability distribution can be expressed by the derivatives of the PGF.

[15] The number of defaults takes on positive integer values n: 0, 1, 2, … For discrete random variable k, the probability of the number of defaults k being equal to a given number n can be represented by function $f_k(n) = P(k=n)=p_n$, $n = 0, 1, 2, \ldots$ Consider the power series formed with the elements of sequence $\{p_n\}$ as coefficients of powers of z: $\eta(z) = p_0 z^0 + p_1 z^1 + p_2 z^2 + \ldots = \sum_{n=0}^{\infty} p(n \text{ defaults})\, z^n$. This can be interpreted as the expected value of z^k, $\eta(z) = E(z^k)$. It is called the probability generating function of k or of the sequence of probabilities $\{p_n\}$. (Berry and Lindgren, p. 107-108).

- If $F_k(z|x)$ is the PGF of k conditional on x, and x has distribution function $H(x)$, then the unconditional PGF is $F_k(z) = \int_x F_k(z|x)\, dH(x)$.

The conditional PGF $F(z|x)$ for the total number of defaults in the portfolio is derived given realization x of the risk factors. For a single loan i, the PGF of the default occurrence is distributed as Bernoulli($p_i(x)$):

$$F_i(z|x) = (1 - p_i(x) + p_i(x)z) = (1 + p_i(x)(z-1)). \tag{3}$$

Using the approximation formula $\log(1+y) \approx y$ for y close to 0, it can be written as

$$F_i(z|x) = e^{\log(1+p_i(x)(z-1))} \approx e^{p_i(x)(z-1)}. \tag{4}$$

The right-hand side is the PGF for a random variable distributed Poisson($p_i(x)$)[16].

Conditional on the risk factors x, default events are independent across loans, so the PGF of the sum of loan defaults is the product of the individual PGFs:

$$F(z|x) = \prod_i F_i(z|x) \approx \prod_i e^{p_i(x)(z-1)} = e^{\mu(x)(z-1)} \text{ where } \mu(x) \equiv \textstyle\sum_i p_i(x). \tag{5}$$

To get the unconditional PGF $F(z)$, the x is integrated out. Suppose that x_k has probability density function $f_k(x)$, so that $P(x \le x_k \le x + dx) = f_k(x)dx$. Then the probability generating function for default events is the average conditional probability generating function over all possible values of the mean default probability according to the following computations:

[16] Poisson process is a model of a process where events arrive at random, and are counted. The rate parameter of a Poisson process $p_i(x)$ is the average number of events in a unit interval (in this case, average default probability over a given time period). The Poisson approximation to binomial probabilities works well when the probabilities $p_i(x)$ are small, and the constraint that a single loan can default only once can be ignored. Binomial probabilities are cumbersome to deal with when the number of loans is large, so using the Poisson approximation is essential to having an analytical solution in the model.

$$F_k(z) = \sum_{n=0}^{\infty} P(n \text{ defaults}) z^n = \sum_{n=0}^{\infty} z^n \int_{x=0}^{\infty} P(n \text{ defaults}|x) f(x) dx = \int_{x=0}^{\infty} e^{x(z-1)} f(x) dx \tag{6}$$

The risk factors x_k are assumed to be independent gamma-distributed random variables with mean μ_k and variance σ^2_k, $k = 1,\ldots,K$. Gamma distribution[17] is selected as an analytically tractable distribution with two parameters. Under the assumption of gamma-distributed risk factors, the probability generating function for the number of defaults in the portfolio is given by[18]

$$F(z) = \prod_{k=1}^{n} F_k(z) = \prod_{k=1}^{n} \left(\frac{1-\delta_k}{1-\delta_k z} \right)^{\alpha_k} \tag{7}$$

where parameters are

$$\alpha_k = \mu_k^2 / \sigma_k^2; \quad \beta_k = \sigma_k^2 / \mu_k; \quad \delta_k = \beta_k / (1+\beta_k).$$

The distribution of defaults in each sector is Negative Binomial. The distribution of default events for the whole portfolio is the sum of the Negative Binomial sector distributions.

The probability generating function $G(z)$ for losses is obtained by combining PGF for the number of defaults $F(z)$ with exposures[19]. The PGF for losses is given by:

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[17] The Gamma distribution $\Gamma(\alpha,\beta)$ is a two-parameter skewed distribution. The Gamma distribution has a long right tail for small values of α. As α increases, the distribution becomes more symmetric and approximates the Normal distribution. If variable X is $\Gamma(\alpha,\beta)$-distributed random variable, its probability density function is given by $P(x \le X \le x + dx) = f(x)dx = \dfrac{1}{\beta^{\alpha}\Gamma(\alpha)} e^{\frac{-x}{\beta}} x^{\alpha-1} dx$ where $\Gamma(\alpha) = \int_{x=0}^{\infty} e^{-x} x^{\alpha-1} dx$ is the Gamma function. The Gamma distribution $\Gamma(\alpha,\beta)$ is a distribution fully described by its mean and standard deviation related to its parameters as follows: $\mu = \alpha\beta$ and $\sigma^2 = \alpha\beta^2$ (CSFP, Appendix 8.2).

[18] See CSFP, Appendix A8 for the proof.

[19] See CSFP, Appendix A9 for the derivation.

$$G(z)=\prod_{k=1}^{K}\left(\frac{1-\delta_k}{1-\delta_k P_k(z)}\right)^{\mu_k^2/\delta_k^2} \quad \text{where} \quad P_k(z)\equiv\frac{1}{\mu_k}\sum_i w_{ik}p_i z^{\nu(i)} \tag{8}$$

The unconditional probability that there will be n units of the standardized loss unit L in the total portfolio is given by the coefficient on z^n in the Taylor series expansion of $G(z)$, $G(z)=\sum_{n=0}^{\infty} p(\text{total losses}=n\cdot L)\,z^n=\sum_{n=0}^{\infty} A_n z^n$. The expansion of $G(z)$ as $A_0+A_1 z+A_2 z^2+\ldots$ follows the recurrence relation[20]

$$A_{n+1}=\frac{1}{b_0(n+1)}\left(\sum_{i=0}^{\min(r,\,n)} a_i A_{n-i}-\sum_{j=0}^{\min(s-1,n-1)} b_{j+1}(n-j)A_{n-j}\right) \tag{9}$$

where $\{a_i\}$ and $\{b_i\}$ are coefficients of polynomials $A(z)$ and $B(z)$ such that $d(\log(G(z))/dz=A(z)/B(z)$. The recurrence relationship is iterated until the number of loss units j^* is reached such that $G(j^*)=A_0+A_1+\ldots+A_{j^*}$ is greater or equal to the desired tail percentile (e.g., 0.995).

When the distribution of losses is known, the portfolio loss at a given percentile (Value-at-Risk) can be allocated across all exposures. Risk contribution of exposure ν_i can be defined as the marginal effect of its presence on the standard deviation of credit losses: $RC_i=\nu_i\frac{\partial\sigma}{\partial\nu_i}=\frac{\nu_i}{2\sigma}\frac{\partial\sigma^2}{\partial\nu_i}$. If risk contributions are defined in terms of portfolio standard deviations, then an analytic formula is possible since risk contributions (defined as above) total to portfolio standard deviation σ. The risk contribution of exposure ν_i is[21]

$$RC_i=\frac{\nu_i p_i}{\sigma}\left(\nu_i+\sum_k\left(\frac{\sigma_k}{\mu_k}\right)^2\varepsilon_k w_{ik}\right) \tag{10}$$

[20] See CSFP, Appendix A10 for the derivation of the recurrence relation.
[21] See CSFP, Appendix A13.2, for derivation.

Risk contributions can alternatively be defined in terms of the marginal effect on a given loss percentile. In this case, risk contributions are approximations. Let ε be the expected loss, σ be the standard deviation of losses, and X be the loss at a given percentile. Then, the multiplier ξ to the given percentile is defined like $\varepsilon + \xi\sigma = X$. Risk contributions to the percentile are defined as

$$R\hat{C}_i = \varepsilon_i + \xi \cdot RC_i \tag{11}$$

where ε_i is the expected loss for exposure ν_i and RC_i is given by (10).

5.2 Overcoming Disadvantages of CreditRisk+

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 section describes how the model can be improved by using a faster and more accurate algorithm, accounting for sector correlations and volatility of the market value of collateral, and including the effects of macroeconomic factors in the estimation of model parameters.

5.2.1 Alternative Algorithm

Wilde (2000, p. 7) describes the problem that arises when CreditRisk+ handles a large number of sectors and obligors. Too fine discretization of exposure sizes and a large number of sectors causes polynomials $A(z)$ and $B(z)$[22] used in the recurrence relationship (9) to be very large, which causes their sums and convolutions to accumulate

[22] See CSFP, Appendix A10 for the definitions of polynomials $A(z)$ and $B(z)$.

round-off errors. Most calculations on a personal computer use 15 significant figures of accuracy, for which rounding errors can become a problem by distorting the loss distribution (Wilde, 2000, p. 611). Another problem one may encounter in implementation of CreditRisk+ model is loss of accuracy because of too coarse a discretization of exposure sizes. Thus, the size of a loss unit needs to be "optimal", which cannot be determined based on the original CreditRisk+ model.

Gordy (2002) developed an alternative algorithm that not only avoids these computational difficulties but also smoothes over the jumps in the original discrete model by generating a continuous loan loss distribution (p. 1353). Gordy finds that the standard algorithm may break down when there are as few as seven systematic risk factors and five thousand borrowers. He shows how to calculate the cumulant generating function (CGF) of the portfolio loss distribution (the logarithm of its moment generating function) and use it for obtaining the moments of the loss distribution. The moments of a loss distribution can be used as a quick diagnostic tool on the implementation of the standard CreditRisk+ algorithm since the numerical accuracy of the moments calculation is not affected by the number of risk factors and discretization of exposures, and the computation is very fast. The cumulants of a loss distribution[23] can be used to check for an imprecision in the calculation of loss distribution due to the choice of exposure unit and due to the rounding errors accumulating in the recursion formulas of the standard solution algorithm. Tail percentiles of a loss distribution (values greater than the

[23] Cumulants are the constants on the Taylor series expansion of the logarithm of a characteristic function. The derivatives of the characteristic function at the zero parameter value are the moment generating function (the n^{th} derivative of the characteristic function is related the n^{th} moment). Cumulants are related to the moments: the first three cumulants are equal to the three first moments of a distribution, but the relationship between cumulants and moments becomes more complex for the higher order cumulants. See Stuart and Ord (§3.12) for more details on cumulants.

expected loss) can be calculated by Saddlepoint approximation based on the cumulants. Gordy compares the alternative algorithm to the standard CreditRisk+ algorithm on a variety of portfolios and concludes that the Saddlepoint approximation is more accurate and robust in the situations when the standard algorithm does not perform well (when the number of customers and sectors is large), and is less accurate in the situations when the standard algorithm is fast and reliable (when the number of borrowers and sectors is small).

Saddlepoint approximation is able to provide more accurate results than the standard algorithm because it uses the exact values for loss exposures rather than discrete values and calculates a smooth continuous distribution that changes continuously in all model parameters.

Saddlepoint approximation is as a tool in statistics to approximate densities or distribution functions. It outperforms other approximation methods with respect to computational costs and accuracy, even at the very extremes of the density and distribution tails. For some distributions, including the gamma, the approximation is exact. Saddlepoint approximation does not make any assumptions about the shape the loss distribution. The method is derived and discussed in Lieberman. See Haaf for the application of saddlepoint approximation methods to credit risk modeling. Saddlepoint approximation is used to approximate tail probabilities in cases when the cumulant generating function is known in analytical form, while the probability density function does not have a tractable form. "In saddlepoint approximation, the density of a distribution $f(x)$ at each point x is obtained by "tilting" the distribution around x to get a new distribution $f^{\prime}(z; x)$ such that x is in the center of the new distribution. The tilted distribution is approximated via Edgeworth expansion, and the mapping is inverted to obtain the approximation to $f(x)$" (Gordy, 2002, p. 1345). The saddlepoint approximation is achieved by comparison with some base distribution that has an analytic CGF and PDF, such as the normal distribution. The entire cumulant generating function of the approximated distribution is used, and it is readjusted at each value of the random variable by the saddlepoint to optimize the fit of the approximation.

First, Gordy (2002, p. 1340) computes the cumulant generating function of a distribution. If $F_y(z)$ is the probability generating function (PGF) of Y, then the CGF $\psi_y(z)$ is given by the log of its moment generating function, $\psi_y(z) = \log(F_y(e^z))$. The j^{th} derivative of ψ_y evaluated at $z = 0$ is the j^{th} cumulant of Y. Cumulants are related to the moments of a distribution. Let m_j be the j^{th} centered moment of distribution Y, or $m_j = E[(Y-m)^j]$. The first five cumulants are related to central moments as follows: $k_1 = m_1$, $k_2 = m_2$, $k_3 = m_3$, $k_4 = m_4 - 3m_2^2$, $k_5 = m_5 - 10m_2m_3$.

Following Gordy (2002, p. 1341-42), the CGF of the loss distribution in the CreditRisk+ model is

$$\psi(z) = \log(G(e^z)) = \sum_{k=1}^{K} \frac{\mu_k^2}{\sigma_k^2} \log\left(\frac{1-\delta_k}{1-\delta_k P_k(e^z)}\right) \tag{12}$$

where $\delta_k = \beta_k/(1+\beta_k)$ and $\beta_k = \sigma_k^2/\mu_k$.

Function $Q_k(z)$ is defined as

$$Q_k(z) \equiv \mu_k P_k(e^z) = \sum_i w_{ik} p_i e^{v_i z}, \tag{13}$$

which is substituted into previous equation, so that the CGF of the loss distribution is

$$\psi(z) = \sum_{k=1}^{K} \frac{\mu_k^2}{\sigma_k^2} \log\left(\frac{\mu_k(1-\delta_k)}{\mu_k - \delta_k Q_k(z)}\right) \equiv \sum_{k=1}^{K} \psi_k(z). \tag{14}$$

Let D be the differential operator ($D^j f(x)$ is the j^{th} derivative of f with respect to x).

For the systematic risk factors, the first derivative of ψ_k is

$$\psi'_k(z) = \frac{\mu_k^2}{\sigma_k^2}\left(\frac{\delta_k DQ_k(z)}{\mu_k - \delta_k Q_k(z)}\right). \tag{15}$$

The expression in parenthesis can be generalized as

$$V_{j,k}(z) \equiv \frac{\delta_k D^j Q_k(z)}{\mu_k - \delta_k Q_k(z)}. \tag{16}$$

Gordy observes that derivatives of V follow the simple recurrence relation,

$$DV_{j,k}(z) = V_{j+1,k}(z) + V_{j,k}(z)\,V_{1,k}(z). \tag{17}$$

Thus, using equations (15), (16) and (17), higher derivatives of ψ_k can be generated. The second derivative is

$$\psi''_k = (V_{2,k}(z) + V_{1,k}(z)^2). \tag{18}$$

To obtain the cumulants, the derivatives of ψ are evaluated at $z = 0$. Using the fact that $Q_k(0) = \mu_k$, expression

$$V_{j,k}(0) = \frac{\sigma_k^2}{\mu_k^2} D^j Q_k(0) \tag{19}$$

is derived and substituted into equations (15) and (18). Gordy shows how the cumulants can be used to detect inaccuracies in the traditional CreditRisk+ algorithm arising due to too fine or too coarse discretization of exposure sizes or the rounding errors. If the first two cumulants calculated using (19) do not match the first two moments computed in the traditional way, it means that the traditional algorithm has failed.

Gordy (2002, p. 1345-1346) suggests estimating the tail of the CreditRisk+ loan loss distribution using the cumulants and Saddlepoint approximation. One of the variants of Saddlepoint approximation is the Lugannani-Rice approximation (see Lugannani-Rice for derivation; see Haas for the application to credit risk modeling). If Y is a random variable with distribution $G(y)$ and CGF $\psi(z)$, and z is the unique square root of equation $y = \psi'(z)$, then the Lugannani-Rice formula for the tail of G is

$$1 - G(y) \approx 1 - \Phi(w) + \phi(w)\left(\frac{1}{u} - \frac{1}{w}\right) \tag{20}$$

where $w = \sqrt{2(zy - \psi(z))}$ and $u = z\sqrt{\psi''(z)}$. Φ and ϕ are the cumulative distribution function and the probability distribution function of the standard normal distribution. Gordy shows that as long as the tail percentile q is greater than the distribution mean $G(\mathrm{E}[Y])$, the bound z_k^* for each systematic sector k must satisfy

$$0 < z_k^* \le \frac{-\log(\delta_k)}{\sum_i \frac{w_{ik} p_i}{\mu_k} v_i}. \tag{21}$$

Since $Q_k(z)$ is strictly increasing in z, it is possible to find z_k^* in the bounded interval. Gordy (2002, p. 1346) specifies the remaining steps as follows:

1. "Set $z^* \equiv \min\{z_1^*, \ldots, z_K^*\}$. Form a fine grid of z values in the open interval $(0, z^*)$." The finer the grid, the more accurate the result, and the slower the program execution. The study computes 100 points on the grid. Stress-testing is performed to compare the resulting Value-at-Risk to that under 1,000 and 10,000 points on the grid.
2. "At each point in the grid, calculate corresponding y, w and u from the derivatives of ψ."
3. "Form a table of pairs $(1\text{-}G(y), y)$ using the Lugannani-Rice formula. Interpolate to find the value of y corresponding to $1\text{-}G(y) = 1\text{-}q$." In the study, linear

interpolation is used. Linear interpolation of points on the cumulative distribution function gives a conservative bias to Value-at-Risk for the approximated points. Thus, increasing the accuracy of the algorithm by computing more points on the tail makes the Value-at-Risk smaller.

Gordy finds that the saddlepoint approximation algorithm is more accurate than the standard algorithm for portfolios over 500 loans regardless of the number of sectors. It is much faster and more robust than the standard recurrence algorithm in practical applications. Also, because it implies a continuous loss distribution curve, risk contributions are better behaved than in the case of the discrete distribution where percentile values change in jumps, and small changes in the loss unit can produce large changes in the marginal tail contributions.

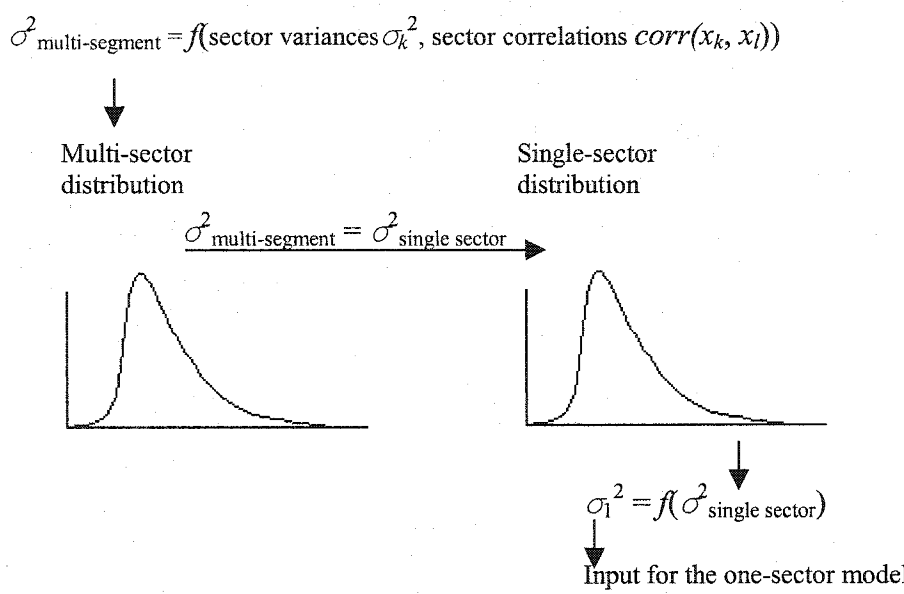
Gordy's alternative algorithm is used by the model in this study. The standard algorithm is also implemented for comparison with the alternative algorithm. The performance of the two algorithms is compared in Section 7.7.2.

5.2.2 Integrating Sector Correlations

One of the shortcomings of the CreditRisk+ model is the assumption of sector independence. In reality, sectors such as industries or geographical regions are influenced by strong correlations. Assuming independent sectors in a model underestimates the amount of required economic capital if there is a positive correlation between sectors.

Wilde (2000) recommends that in case of using multiple independent sectors, volatilities of default probabilities need to be higher than the observed ones so that they counteract the tendency of sectors to reduce volatility of default probability: "To use more than one sector, one should expect to compensate for this with higher individual sector volatilities, giving a similar overall estimate of risk" (p. 614). However, Wilde does not provide any guidance on the procedure. Wilde (2000) observes that under multiple sectors, the loss distribution looks a lot like the result of using one sector, but risk contributions are more accurate at the transaction level.

Figure 5.2: Accounting for Sector Correlations



Bürgisser, Kurth, Wagner and Wolf present a framework for extending CreditRisk+ by accounting for correlations between sectors. In a nutshell, they account for correlations at the cost of less accurate risk contributions. They use a one-sector model with the sector variance equal to the one of a matching multi-segment distribution (see **Figure 5.2**). This approach is taken because, first, there is no unique representation of a multi-dimensional gamma distribution, and second, due to the scarcity of data that would be needed to fully specify multi-dimensional distributions. Bürgisser et. al. take the correlation structure into account by the first two moments of the loss distribution, the mean ε and the standard deviation σ. They use the fact that the mean and the standard deviation of a loan loss distribution are independent of the distribution of the risk factors:

$$\varepsilon = \sum_i p_i \, v_i \quad \text{and} \quad \sigma^2 = \sum_{k=1}^{n} \varepsilon_k^2 \left(\frac{\sigma_k}{\mu_k} \right)^2 + \sum_i \varepsilon_i v_i \tag{22}$$

In the case of the only systematic risk factor, the variance of a loan loss distribution is

$$\sigma^2 = \frac{\sigma_1^2}{\mu_1^2} \varepsilon_1^2 + \sum_i \varepsilon_i v_i \tag{23}$$

The "multi-segment variance" σ^2 is required to be equal to the variance of a matching distribution for a single systematic factor, $\sigma^2_{\text{multi-segment}} = \sigma^2_{\text{single sector}}$. The multi-segment variance is based on the covariance matrix of sector default probabilities. In the case of two segments, it is calculated using formula

$$\sigma^2 = \sigma_1^2 + \sigma_2^2 + 2Cov_{1,2} \tag{24}$$

where σ_1^2 and σ_2^2 are variances of risk factors in segments 1 and 2.

After equating portfolio variances of the multi-segment and single-segment distributions, the only systematic factor's variance σ_1^2 in the single-sector distribution is extracted from the following condition:

$$\frac{\sigma_1^2}{\mu_1^2} \varepsilon^2 = \sum_k \frac{\sigma_k^2}{\mu_k^2} \varepsilon_k^2 + \sum_{\substack{k,l \\ k \neq l}} Corr(x_k, x_l) \cdot \frac{\sigma_k}{\mu_k} \cdot \frac{\sigma_l}{\mu_l} \cdot \varepsilon_k \cdot \varepsilon_l \tag{25}$$

Overall loss distribution is then calculated in the usual way using the mean ε and variance σ_1^2 of the single sector approach as the parameters determining the gamma distribution (Kurth, Taylor, and Wagner, p. 245).

The risk contribution for loan i in sector k, defined by (10), then becomes:

$$RC_i = \frac{p_i E_i}{\sigma}\left[\frac{\sigma_k^2}{\mu_k^2}\varepsilon_k + \sum_{l:l\neq k} Corr(x_k, x_l)\cdot\frac{\sigma_k}{\mu_k}\cdot\frac{\sigma_l}{\mu_l}\cdot\varepsilon_l\cdot w_{ik} + E_i\right] \tag{26}$$

The disadvantage of the method Bürgisser et. al. suggest is that the matched dependence structure is given by one volatility, which turns out to be an average of the segment volatilities (Kurth and Tasche, p.7). Applying one volatility for the entire portfolio causes a shift of risk contributions to the average (Kurth and Tasche, p. 9). Giese gives an example of this approach yielding insensible results when the loan distribution in the portfolio is very skewed, and proposes an alternative methodology that can handle uniform correlations between risk factors a lot better. However, Giese's assumption about uniform correlation between risk factors limits the usefulness of his approach.

The approach that Bürgisser et. al. take seems to be more pertinent to our case of sectors - agricultural industries that have various degrees of correlation with each other. As will be shown in Chapter 6, defaults within the traditional farm industries (between crop and various livestock industries) and within the general farm industries (agricultural businesses, rural residence) are positively correlated, while defaults between the traditional farm industries and the general economy industries appear to be independent.

5.2.3 Variations in Loss Given Default

The CreditRisk+ model assumes that loss given default (LGD) is a non-variable value (default severities are deterministic). This assumption may tend to bias downward the estimated tail of the probability density function of credit losses (Basel Committee on Banking Supervision, 1999, p. 37). Wilde shows (2000, p. 617) that the contribution to overall portfolio risk made by recovery rate volatility is not significant under assumption that recovery rates are independently distributed. For the most part, this assumption is true since various studies on variations of default severities over time suggest that the non-systematic component is dominant in these data (Bürgisser, Kurth, and Wagner, p. 23). However, in highly collateralized portfolios, a common shift in collateral value can significantly increase the level of portfolio risk. In agricultural lending, collateral is typically real estate, land, or chattel (collateral other than real estate, such as farm equipment, livestock, crops, etc.). Chattel is mostly affected by non-systematic factors that tend to cancel each other out, while real estate may be affected by common factors.

Bürgisser, Kurth, and Wagner propose an approach that incorporates the risk of devaluation of the collateral. Their framework is based on segmentation by industry and collateral type. Similar to the approach of Bürgisser, Kurth, Wagner and Wolf in accounting for sector correlations, the approach of Bürgisser, Kurth, and Wagner reduces a multi-segment structure to a single segment with the same variance. Variance of the loan loss distribution with the single segment is based on the variance of the distribution with multiple segments and correlations between the segments. Single-segment variance of default probability is then used to calculate the full loss distribution assuming one segment.

Additional data requirements are non-systematic and systematic volatility of LGD. Volatilities of default severities in the literature are mostly based on bond default data and would differ from parameters required by agricultural lenders. Reasons for these differences are different client types, the bank's internal process for workout, and collateral types. Since the estimates of the volatilities of default severities in agriculture are nearly impossible to come by (because of scarcity of data), this enhancement of the

CreditRisk+ model is not implemented in the study. However, this approach may be implemented in the future when more data on loan defaults and losses become available. It would be desirable to accumulate data over longer time series and more lending institutions for meaningful estimates of LGD volatilities. To account for collateral volatility, this study takes LGD rates to be reasonably conservative estimates. This approach is consistent with the treatment of LGD volatility by the New Basel Capital Accord. As CreditRisk+ documentation (CSFP) suggests, stress testing is performed on recovery rates to analyze the effect of increased LGD rates on the loan loss distribution. For example, a stress test where LGD rates increase by 50% for the loans collateralized by land can be representative of land devaluation that occurred during the events of 1980s. A stress test where all LGD rates are equal to 100% (no recoveries) can be used to analyze the situation of extreme losses in the event of default.

5.2.4 Incorporating Macroeconomic Factors

Usually default probabilities for portfolio credit risk models, including the CreditRisk+ model, are obtained by calculating historical averages of default probabilities, assuming that these probabilities will stay the same in the future.

Boegelein et. al. propose an approach of estimating default probabilities using the method of Seemingly Unrelated Regressions (SUR). They implement this method consistently with the CreditRisk+ model's assumptions by relating the development of default probabilities to changes in systematic risk factors. They show that default probabilities within each sector can be explained to a great extent by the changes in underlying macroeconomic risk drivers such as interest rates, growth rates of GDP, unemployment rate, etc.

In a system of seemingly unrelated regressions, there are M individual models

$$y_i = X_i\beta_i + \varepsilon_i, \quad i = 1,\ldots, M$$

where y_i is a $(T \times 1)$ – vector of transformed default probabilities (logits) $\ln\left(\dfrac{default\ probability_{it}}{1-default\ probability_{it}}\right)$ for M sectors, i. e. industries. X_i is a $(T \times K_i)$ – matrix of risk factor values. ε_i is a $(T \times 1)$ – vector of random errors. T denotes the number of time periods. β_i is a $(K_i \times 1)$ – vector of regression parameters. In general, each equation does not have the same number of risk factors. It is assumed that $E(\varepsilon) = 0$. The covariance matrix of the errors is assumed to be represented by $Cov(\varepsilon_i, \varepsilon_j) = E(\varepsilon_i\, \varepsilon_j') = \sigma_{ij}\, \boldsymbol{I}_T$, where $\boldsymbol{I}_T$ is the $(T \times T)$ identity matrix. These assumptions imply that the errors are correlated in the same time period, but not correlated across different time periods. Then the default probabilities may also be correlated for a given time period and given values of risk factors.

Boegelein et. al. estimate each of the M sector-specific equations using Ordinary Least Squares (OLS). Then they compute the SUR estimator for the M equations using OLS residuals and a consistent estimator of the residuals' covariance matrix.

Boegelein et. al. use quarterly data on default probabilities from national statistics offices in several countries. Defaults in 5 industries (agriculture, commerce, construction, manufacturing, and services) are analyzed in each country for 1980-1999. Sectors represent country/industry combinations. Boegelein et. al. use a variety of publicly available macroeconomic indices in the areas of capital market, consumption, employment, foreign investments, governmental activity, income, prices and value added to capture systematic influences on default probabilities. The effects of risk factors are investigated for different time lags ranging between one and nine quarters. The time lag resulting in the highest partial correlation between each risk factor and default probability is used for each risk factor. Lagged dependent variable is also included in the pool of predictors, representing the default probability's persistence. For example, the default probability in U.S. manufacturing depends on the long-term government bond yield (4 quarters lag), growth rate of GDP (2 quarters lag), the growth rate of industrial production (7 quarters lag), and a lagged dependent variable (1 quarter lag).

In the CreditRisk+ technical document, default probabilities in the next time period are forecasted to be equal to their historical average. The standard deviation of default probability is the measure of error associated with the forecast. Boegelein et. al. argue that the average-of-the-past approach has a high degree of model risk, with forecasts being correct on average, but not very accurate for any particular year. The results of the SUR analysis can be used for the segment-specific forecasts of default probabilities, given the current values of the corresponding macroeconomic risk factors.

The CreditRisk+ model requires default probabilities for each borrower. To include the effect of systematic risk in the borrower's sector, Boegelein et. al. suggest multiplying the borrower's historical average default probability by a scaling factor. The factor represents the segment-specific forecast of default probabilities relative to their historical average.

The SUR analysis can also be included in estimating the correlation matrix of default probabilities between sectors. Boegelein et. al. replace the correlation matrix of default probabilities between the sectors by the correlation matrix of SUR residuals. Correlations can be perceived to be high if there are common systematic risk factors influencing co-movements of default probabilities. Identification of these factors and removal of their effects on the correlation structure significantly reduces correlations between sectors. Boegelein et. al. recommend using the correlation matrix of SUR residuals to identify meaningful segments for CreditRisk+ models. Using the 95th level of confidence, they test the hypothesis that sectors are independent conditional on the state of the economy.

CreditRisk+ model requires default standard deviation for each sector as an input. Boegelein et. al. estimate sector volatilities of default probabilities from the forecast standard errors including the correlation matrix of the SUR residuals. This procedure results in significantly lower standard deviations than the 50-100% of mean default probability associated with the average-of-the-past forecast.

In a nutshell, Boegelein et. al. show how incorporating the effect of macroeconomic variables can make CreditRisk+ parameters more accurate, resulting in more precise forecasts of default probabilities, sector standard deviations, and the correlation matrix between sector default probabilities. This procedure may significantly reduce economic capital requirements.

Application to Agricultural Lending

Bjornson and Innes study the effect of macroeconomic factors on asset returns in agriculture using capital asset pricing models (see Cochrane for more information on asset pricing). They analyze the sensitivity of agricultural returns to the following macroeconomic factors: inflation (unexpected inflation variable and changes in expected inflation), stock market performance, index of industrial production, and interest rates (bond default risk premium and bond maturity risk premium) (see Bjornson and Innes for definitions). These and other systematic factors can be used in a Boegelein et. al. – type analysis to incorporate the effects of macroeconomic variables in calibration of parameters when longer time series of default data becomes available over time. This enhancement is not implemented in this study because of insufficient data series for meaningful SUR estimation procedure at this point in time.

5.3 Implementing the Model

The following aspects of model implementation are covered: using loans versus borrowers as a unit of analysis, industry assignments, handling defaulted loans, accounting for market and operational risk, calculations, and spreadsheet implementation.

Loans versus Borrowers as a Unit of Analysis

CreditRisk+ technical document for simplicity assumes that each borrower has one exposure. In reality, each borrower may have several loans with different collateral, maturity, and of different type (operating loans, real estate, lease). A borrower may default on one loan or several loans: there is some correlation in defaults to the same borrower, but it is not perfect correlation. A borrower is more likely to default on a less significant loan with a smaller collateral. A borrower usually defaults on all of the loans if he/she declares a bankruptcy, and defaults on one of the loans during a less drastic shortage of repayment resources.

There are two approaches available to the problem of multiple loans per borrower: to assume that loan defaults to the same borrower are independent, or to assume that defaults to the same borrower are perfectly correlated. Under the first approach, loans to the same borrower are treated at separate independent exposures. Under the second approach, loans to the same borrower are combined into one exposure. The approach affects the definition of a risk contribution: the first approach produces loan risk contributions, while the second approach produces borrower risk contributions.

This study chooses the first approach, assuming that loan defaults to the same borrower are independent, since the ratio of the number of loans per borrower is relatively low (1.75 loans per borrower as of 12/31/2002). Loan risk contributions are preferred by lenders to borrower risk contributions since loan risk contributions are important determinants for loan pricing and assigning economic capital and allowance across loans with different loan types and LGD ratings. If a lending institution believes that the assumption of perfectly correlated defaults to the same borrower is more appropriate, exposures can be grouped by borrower as a sum of loan volumes adjusted by LGD rates. Alternatively, a lending institution may decide to increase default probabilities for the non-defaulted loans to the borrowers who defaulted on some of their loans. A small number of defaulted loans in AgStar's database currently does not allow for the estimation of default probability of the loans that are not in default conditional on the event of the borrower defaulting on some of its loans. If default data were available from several lenders with a large total number of defaulted loans, this conditional probability could have been estimated and included in the analysis.

Industry Assignments

Since CreditRisk+ model does not have any guidance on how to determine sectors and risk weights, implementations of the model are either based on a single generic sector (e.g. Gordy (2000); Balzarotti, Falkenheim, and Powell; Balzarotti, Castro, and Powell), or rather arbitrary assignment of sector weights, thus creating an additional source of uncertainty (Kurth and Tasche). For example, Lehrbass determines sector weights in the following way: 100% for the sector if there is only one sector for the borrower, 80% and 20% of there is one additional sector, and 70%, 20% and 10% if there are three sectors.

Among lenders, sectors are usually thought of as industries or geographical regions, since these characteristics have the most effect on borrowers' risk. FCS associations have very regionally concentrated portfolios by virtue of their purpose: to serve agricultural clients in specified regions. This causes most borrowers to be highly correlated by geographic location. Industry is considered to have most impact on borrower's default probability. Thus, the study assumes that sectors are synonymous with industries.

To account for borrower-specific (nonsystematic) risk, one of the sectors can be modeled as a specific risk sector with zero volatility of default probability, reflecting the fact that specific risks tend to cancel out in a large portfolio. With the assumption of a single systematic factor, the weight on the specific risk factor can be uniquely determined based on the volatility of default probability. Based on rating agency historical data, this leads to the result that higher quality borrowers have a lower proportion of unsystematic risk and a higher portion of systematic risk than the lower quality borrowers (Gordy, 2000). This result agrees with the finding of Das et. al. who conclude that default probabilities of high quality firms are the most highly correlated, implying that higher quality borrowers have less unsystematic risk.

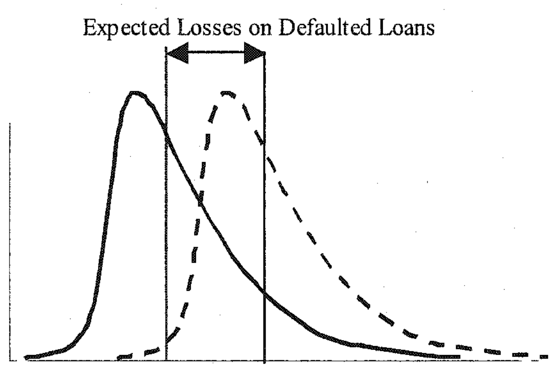
The study ignores borrower-specific risk for several reasons. First, there are multiple industries. This does not allow specific sector weight to be uniquely determined. Using arbitrary borrower-specific sector weights in the absence of guidance on determining sector weights would introduce an additional source of uncertainty. Second, having no borrower-specific risk generates a more prudent estimate of Value-at-Risk. Since the borrower-specific risk is modeled as a sector with zero volatility, assigning some weight to this sector decreases portfolio risk and economic capital requirements. Third, borrower-specific risk does not matter in a large portfolio without huge single exposures. The loss distribution of a large portfolio is mostly determined by systematic effects. Bürgisser et. al. (2001, p.20) shows that in large loan portfolios (of the order of 10,000) the loss distribution approaches an explicit limit distribution depending on the portfolio only through the expected segment losses, regardless of borrower-specific default probabilities. Wilde (2000) also shows that in large portfolios (over 1,000 borrowers) systematic risk and total risk are nearly identical if there are no very large single exposures.

In AgStar's database, each customer is assigned to one industry corresponding to the customer's primary activity. Therefore, each borrower in the study is fully assigned to the industry specified by the AgStar's database.

Handling Defaulted Loans

As Bürgisser, Kurth, and Wagner note (p. 19), the group of loans that have defaulted but have not been resolved should be accommodated by introducing an additional subportfolio with default probability equal to one and zero default volatility. Inclusion of defaulted loans in the model would be inappropriate since the Poisson approximation is valid only for small default probabilities. The mean of loss distribution should be increased by expected losses on defaulted loans (net of realized losses to avoid double-counting), as shown on **Figure 5.3**. Expected loss on a defaulted loan is the exposure less any charge-offs.

Figure 5.3: Shift in Loan Loss Distribution Due to Defaulted Loans



The shift in loan loss distribution increases the mean and Value-at-Risk by the expected losses on defaulted loans, but does not affect economic capital. Intuitively, this shift can be explained by the fact that defaulted loans do not contribute to economic capital since they represent expected loss, while economic capital is intended to cover unexpected loss.

Accounting for Market and Operational Risk

Allowance is supposed to cover expected and probable losses, while capital is supposed to cushion potential losses resulting from credit risk plus losses from any other source rather than credit risk, such as market risk or operational risk (FCA Examination Manual). Total economic capital is assumed to be the sum of credit risk capital (Value-at-Risk – expected loss), market, and operational risk capital.

Calculations

- Total exposure = sum of all loan volumes.
- Maximum loss (total net exposure) = sum of all exposures (loan volume times percentage LGD).
- Mean, standard deviation, skewness and kurtosis of the loan loss distribution are calculated according to Gordy's approach (discussed in section 5.2.1) using a cumulant generating function.
- Value-at-Risk (credit risk funds) is calculated according to the combination of approaches described in section 5.2 and implementation issues in section 5.3.
- Economic Capital = Value-at-Risk – Mean (expected loss) + market risk capital + operational risk capital.
- Loan risk contributions to portfolio standard deviation are calculated according to equation (26) in section 5.2.2. Loan risk contributions to Value-at-Risk are approximated according to equation (11) in section 5.1.

- Loan risk contribution to economic capital = loan risk contribution to Value-at-Risk – expected loss on the loan + market and operational risk capital per dollar of loan volume times the loan volume.
- Economic capital per sector = sum of risk contributions to economic capital by all loans in the sector.

Spreadsheet Implementation

The model is implemented in Microsoft Excel® using Visual Basic code. It uses several worksheets for input and several other worksheets for output. Loan data (loan number, customer number, volume, unfunded balance, default status, industry, loan type, customer involvement, risk rating, loss given default rating) are placed one worksheet. Parameters (default probability for each risk rating, percentage loss given default for each loss given default rating, and minimum exposure) are placed in another worksheet. The program processes the loan data and the parameters and places the outputs in three worksheets. The first output sheet contains the resulting loan loss characteristics (mean and tail percentiles), which represent allowance and capital requirements for the overall portfolio. The second sheet reports allowance and capital requirements for each loan. The third sheet shows the allowance and economic capital requirements for each sector. The market risk capital and operational risk capital are added to the credit risk capital, and the total is compared to the book value of capital. The allowance for loan loss requirement is compared to the book value of the allowance for loan loss.

CHAPTER 6

MODEL PARAMETERIZATION

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.

The majority of FCS associations have historical data of similar or shorter length and with identical loan and borrower characteristics.

Most of the parameters required by the model are the parameters required for the IRB 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. Most of AgStar's clients satisfy the Basel definition of corporate exposures[24]. Besides, all exposures that do not specifically meet one of the definitions should be categorized as corporate exposures (Basel Committee for Banking Supervision, §152). Conservative assumptions are made where necessary, since "where only limited data is available… the bank should adopt a conservative bias" (Basel Committee for Banking Supervision, 2001, §276, p.53).

Basel recommends that all parameter estimates are forward looking, and at the same time have some grounding in historical experience. They should be conservative

[24] "In general, a corporate exposure is defined as a debt obligation of a corporation, partnership, or proprietorship. Exposures to corporates are characterized by the fact that the source of repayment is based primarily on the ongoing operations of the borrower, rather than the cash flow from a project or property," (Basel Committee on Banking Supervision, 2001, §153, p.32). There is a small volume of personal loans in the data set. Personal loans are treated like corporate exposures for simplicity.

estimates of the average parameters (EAD, LGD, PD) over a sufficiently long period of time. However, banks are free to use more conservative estimates if they wish, such as those associated with stress conditions. Estimates must be recalculated when new information becomes available, usually on an annual basis.

In this chapter, the definition of default is given first. Then model parameters (exposures at default, probabilities of default and their standard deviations for each risk ratings, loss given, and correlations of default between industries) are determined.

6.1 Definition of Default

The New Basel Capital Accord (§272) proposed definition of a default event in the IRB framework as when one or more of the following events have taken place: 1) It is determined that the obligor is unlikely to pay its obligations in full; 2) A credit loss event happened such as a charge-off, specific provision, or distressed restructuring involving the forgiveness or postponement of principal, interest, or fees; 3) The obligor is past due more than 90 days on any credit obligation; 4) The obligor has filed for bankruptcy or similar protection from creditors.

The first condition, unlikeliness to pay obligations in full, is consistent with the definition of nonaccrual loans[25] in the U.S. and in particular within AgStar. According to

[25] Accrual basis of accounting is the accounting method in which expenses are recorded when incurred, whether paid or unpaid, and income is recorded when earned, whether received or not received. When a loan is placed in nonaccrual status, accrued interest is reversed to the extent principal plus accrued interest before the transfer exceeds the net realizable value of the collateral. Any unpaid interest accrued in a prior year will be capitalized to the recorded investment of the loan. Cash received on nonaccrual loans is applied to reduce the recorded investment in the loan asset except in those cases where the collection of the recorded investment in fully expected and the loan does not have any unrecovered prior charge-offs. Nonaccrual loans may be returned to accrual status when principal and interest are current, prior charge-offs have been recovered, the ability of the client to fulfill the contractual repayment terms is fully expected, and the loan is not classified doubtful or loss.

AgStar Financial Services (2002), "Loans are placed in nonaccrual status when principal or interest is delinquent for 90 days or more (unless well secured and in the process of collection) or circumstances indicate that full collection is not expected" (p. 14).

Consistent with the Basel definition and its interpretation by the Farm Credit System, this study assumes that a borrower is in default if: s/he files for bankruptcy or foreclosure, or if one or more of his/her loans or leases 1) became nonaccrual or 2) delinquent 90 days or more or 3) have a charge-off or 4) become subject to distressed restructuring.

This definition of loss is used consistently in determining probability of default, exposure at default and loss given default.

6.2 Exposure at Default

Exposure at default (EAD) is defined as the expected exposure upon default of the obligor (Basel Committee for Banking Supervision, 2001, §366). Exposure is measured as the nominal outstanding balance for on-balance sheet items (Basel Committee for Baking Supervision, 2001, §230), which in this study is projected by loan volume[26] as of 12/31/2002.

Off-balance sheet items such as commitments also represent credit risk. A commitment is an amount the lender has legally committed to lend at the borrower's request up to the full amount of the commitment. Commitments consist of two portions:

[26] If a loan is in accrual status, then its volume is equal to the total legal obligation (current principal + interest due + late charges past due + other charges – escrow balances). If a loan is in non-accrual status, then its volume is defined as (current principal + interest due + late charges + other charges + stop accrual + stop late charges – principal charged off – interest charged off – late charges charged off + principal recovered + interest recovered + late charges recovered + other charges recovered + fees recovered – compromise principal).

drawn and undrawn. The drawn portion of commitment should be treated as part of the amount currently borrowed. In the event of default, the drawn commitment is also subject to loss. The undrawn portion of the commitment is a call option, which the borrower can exercise at any time, and not entirely a loan (Ong, p. 97). It is in the borrower's best interest to draw on the committed line of credit when he encounters financial difficulties. This can be possibly explained by the lack of alternative and cheap funding sources resulting from credit deterioration (Ong, p. 100). However, the commitment is not always fully drawn upon in the event of default. The IRB foundation approach recommends including 75% of unfunded commitment into exposure at default. Thus, exposures at default in the study equal to the sum of loan volume and 75% of unfunded commitment.[27]

Exposures at default exclude loans sold to other lenders (having negative volume in the AgStar database) and include exposures purchased from other lenders. Net exposures are calculated for "Master" agreements. A loan originated by AgStar that is partially sold to other lenders is marked as a "Master" loan and has a positive volume. The sold portion has a negative volume. The sold loan number is different from the Master loan number, but has the same CIF (customer ID) in most cases. In these cases, net volumes and unfunded commitments are calculated as sums of volumes and unfunded commitments of master loan(s) and sold part(s)[28] for the same customer ID, loan type, and cost center[29]. When customer ID on the Master loan differs from the customer ID of

[27] AgStar defines unfunded balance in the following way: it is equal to the original contract amount minus current principal if the loan is revolving line of credit, to the original contract minus original principal minus advances to date if the loan is non-revolving line of credit, and to zero if the loan does not have line of credit.
[28] See **Query B.4** in Appendix B.
[29] Cost center number is assigned to loans for general ledger purposes.

sold loan (for 2-3 participations), it is impossible to identify what sold loans belong to what master agreement. For these 2-3 exceptions, master loans are used, and sold loans with negative volumes are ignored.

Volumes are adjusted for participations with AgriBank, Commercial Finance Group, and ProPartners Financial based on fixed percentages received from AgStar. Volumes for leases are adjusted based on fixed percentages for various branch numbers.

After selecting active loans and leases (not paid) as of 12/31/2002, there are 29,214 exposures, including: 26,211 loans, 2,675 leases, and 328 loans net of participations, whose volumes and unfunded balances are equal to the sums of master and sold loans to the same customer ID, loan type, and cost center.

Minimum exposure of $10 (sum of volume and 75% of unfunded commitment) is assumed since late charges are not accessed if less than $10 is due. Past due items less than $10 are not considered past due for the purpose of calculating past due items, days late, and payments late (AgStar Financial Services, 2001, p. 19). There are 28,662 exposures after eliminating exposures below $10. Based on the definition of default, 332 exposures are in default, and 28,330 exposures are not in default on 12/31/2002.

6.3 Default Probabilities and Their Volatilities

Default probabilities and their standard deviations are required for each client. Since a client's risk-rating grade represents his default probability, default probabilities and their deviations are calculated for each risk rating.

6.3.1 Risk Ratings

Risk-rating model represents a scheme for ranking borrowers' creditworthiness based on financial and non-financial characteristics. It is usually a weighted sum of scores based on borrower characteristics. AgStar's risk ratings are based not only on borrower financials (owner equity, working capital to average gross income ratio, repayment capacity) but also on previous repayment history and subjective factors such as stability of the operation. AgStar assigns risk ratings to customers with large loans (over $100,000). Risk ratings range from highest quality (1) to loss (9). Risk-rating schemes categorize borrowers into acceptable ranges A1 through A4. Loan applications are declined for clients of lower quality. When creditworthiness downgrades below the acceptable level, lower risk ratings are assigned according to AgStar guidelines.

Risk ratings are assigned as follows (AgStar Financial Services, 2001):

A1 – "Acceptable". Borrowers of highest quality.

A2 – "Acceptable". Borrowers with a modest degree of risk.

A3 – "Acceptable". Borrowers with smaller margins of debt service coverage and some elements of reduced strength.

A4 – "Acceptable". Borrower with decreased earnings, strained cash flow, increasing leverage and/or weakening market fundamentals that indicate above average risk.

M5 – "Special Mention". Borrower's assets are currently protected but potentially weak. The asset must have a risk that is increasing beyond that at which the loan originally would have been granted.

Adverse classification categories are "substandard", "doubtful", and "loss".

S6 – "Substandard Viable". Substandard loans must have well-defined serious or significant weaknesses that jeopardize debt liquidation.

S7 – "Substandard Nonviable". Ultimate payoff of loans is expected to be achieved through liquidation of collateral.

D8 – "Doubtful". This classification has the same weaknesses as the substandard class plus the characteristic that collection in full is improbable. The probability of loss is high, but the classification as a loss is deferred until the exact status and amount can be determined.

L9 – "Loss". Assets that are considered uncollectible.

Risk ratings can have a trend indicator, such as "S" for stable, "I" for improving, and "D" for deteriorating. In this study, the trend indicator is ignored.

This model has been validated "based on internal and external audits" (Berseth), and it sufficiently discriminates between borrower probabilities of default, as it is shown later in the chapter.

Small (over the counter)[30] loans are credit-scored based on automated Fair Isaac Credit Bureau scores. The credit-scoring model is proprietary and not released to the public. Credit scores effectively provide a rank-order for default risk based on a study that used 1995-1999 data in the Seventh District (AgriBank). Credit scores automatically reclassify depending on delinquency status (on the number of days past due). Credit scores generated by the scorecard range from 200 to 800. Loan applications are declined for customers with credit scores below 200. If an acceptable loan is downgraded, a credit score below 200 can be assigned by an override process. There is a

[30] Small loans are defined as less than $100 thousand.

mapping between credit scores and risk ratings that depends on loan type. It maps credit scores into risk ratings A1 through M5, assuming that credit scored loans are of acceptable quality. The reason for that is that credit risk on small loans is usually reduced by non-farm income sources (AgStar Financial Services, 2002).

AgStar assigns risk ratings to borrowers and to loans. Borrower-level risk rating "is a rating assigned to a customer that reflects the level of risk associated with that customer's ability to repay all outstanding loans" (AgStar Financial Services, 2000, p. 82). Risk ratings for loans are typically determined by the borrower risk ratings. When borrower risk-ratings change, loan risk-ratings update to the borrower risk ratings except for the cases when loan risk rating is manually overridden. This happens when a loan is well protected (for example, by government guarantees or derivatives). Such loans have acceptable risk ratings even if the customer has substandard risk ratings. Thus, loan-level risk ratings may reflect not only borrower's probability of default, but also loss given default. The way of assigning loan risk ratings will change in the future when the degree of compliance with the New Basel Capital Accord increases within the Farm Credit System. The new "two-dimensional" rating system requires one rating dimension to reflect borrower's PD, regardless of the structure and type of loan, and the second rating dimension to be based on specific features of the loan reflecting loss given default (maturity, guarantees) (Basel Committee for Banking Supervision, 2001, §238-239).

Unfortunately, borrower risk ratings have been available in AgStar's database only since 2000. It is assumed that loan risk ratings adequately represent borrower risk ratings for 1998 and 1999 ignoring the fact that loan risk ratings may show that a borrower is more creditworthy than he/she actually is if his/her loan is well protected by derivatives or government guarantees. If a borrower has several loans, the borrower's risk rating is assumed to be the lowest of all the loan risk ratings for that customer, since loans with better risk ratings are covered by guarantees or other special provisions.

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 (see **Table 6.1**): 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).

Table 6.1: Distribution of Loans by the Type of Risk Rating Used

Type of Risk Rating	By Loan Volume	By Number of Loans
Borrower risk rating	77.60%	57.40%
Loan risk rating	13.30%	18.10%
Mapped credit score	8.50%	21.30%
None, converted to RR 3	0.60%	3.20%

6.3.2 Probabilities of Default

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 for Banking Supervision, 2001, §270). Estimates of PD must represent a conservative view of a long-run average PD. Preferably, default probabilities should be calculated based on at least a whole economic cycle. However, AgStar' s data is sufficient to satisfy Basel's requirement of the minimum of 5 years of historical observations to estimate probability of default.

Consistent with the New Capital Accord and the assumption of annual time horizon in the credit risk model, annual default probabilities are computed: the probability that a borrower will default over a given year. A lender will typically analyze the data for a given year-end to calculate economic capital for the next year using the model. Since probabilities of default are known and equal to one for defaulted loans, the lender is interested in assigning default probabilities to non-defaulted loans. Thus, default probabilities should reflect the percentage of borrowers who are not in default in the beginning of the year that will default during the year. Only non-defaulted borrowers with loans that are not fully paid off are included. As an example, **Query B.1** in Appendix B selects non-defaulted customers risk rated 1 in 2001. **Query B.2** selects defaulted customers risk rated 1 in 2002. Annual default probability for each borrower risk rating is calculated as the ratio of the number of customers whose loans defaulted over a given year to the number of non-defaulted customers with unpaid loans in the beginning of the year. Risk rating for the beginning of the year is used, since default event can change the risk rating during the year. This procedure is consistent with the classic Moody's procedure of calculating issuer-weighted default rates.

For example, there were 1,617 non-defaulted borrowers with unpaid loans in risk rating 4 as of 12/31/2001. Eight borrowers out of 1,617 defaulted between 12/31/2001 and 12/31/2002. Thus, the default probability is 8/1,617 = 0.5% in 2002 among borrowers of risk rating 4. See **Table A.1** in Appendix A for the annual statistics on defaults per risk rating grade in 1998-2002. This data is used to calculate mean default probabilities (see Column 2 of **Table 6.2**). From comparing mean defaults for different risk ratings, we observe that AgStar risk ratings show discriminatory power between the ratings. Default probabilities increase for lower risk ratings.

Table 6.2: Actual and Fitted Default Probabilities and Their Standard Deviations by Risk Rating

Risk Rating	PD Historical	St. Dev. Of PD 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 hard 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. One way to smooth the default probabilities and fill the blanks is to simply use judgment. For example, Gordy (2000, p. 25) used his judgment on S&P data to determine default probabilities for the highest two bond ratings (AAA and AA) that did not have any defaults in 1981-97. He assumed that default probabilities for grades AAA and AA were higher than those based on a sample. He also assumed that default probability for grade A was lower than that based on the sample since there were only 5 defaults in this grade, which caused considerable imprecision.

Another 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. **Figure 6.1** (solid line) shows historical mean values of default probabilities for each of the risk ratings. Default probabilities increase exponentially with the increase in risk ratings. This confirms "strong evidence from various empirical default studies that default frequencies grow exponentially with decreasing creditworthiness" (Bluhm, Overbeck, and Wagner, p. 23). Default probabilities show almost a linear trend on logarithmic scale (**Figure 6.2**, solid line). This is a clue that logarithmic transformation of 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[31], an exponential function is estimated that is used to calculate smoothed default probabilities:

$$Ln(PD) = -7.211 + 0.827 * \text{Risk Rating}.$$

[31] There are no outliers, influential observations, or problems with heteroscedasticity. The regression has a very good fit as the table below shows.

Summary Output for Predicting PD as a Function of Risk Rating

Regression Statistics	
Multiple R	0.992243309
R Square	0.984546785
Adjusted R Square	0.981456142
Standard Error	0.245243001
Observations	7

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	19.1593494	19.159349	318.55727	1.01353E-05
Residual	5	0.300720647	0.0601441		
Total	6	19.46007005			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
Intercept	-7.21060119	0.207268166	-34.788754	3.692E-07	-7.7434001	-6.67780228
X Variable 1	0.827201595	0.046346571	17.848173	1.014E-05	0.708064137	0.946339053

If there were no defaults among borrowers in the highest risk ratings in the sample, the regression could have been used to estimate default probabilities for these risk ratings. The fitted values for AgStar (dashed line in **Figure 6.1** and **Figure 6.2**) are reported in Column 4 of **Table 6.2**.

Figure 6.1: Default Probabilities on Linear Scale

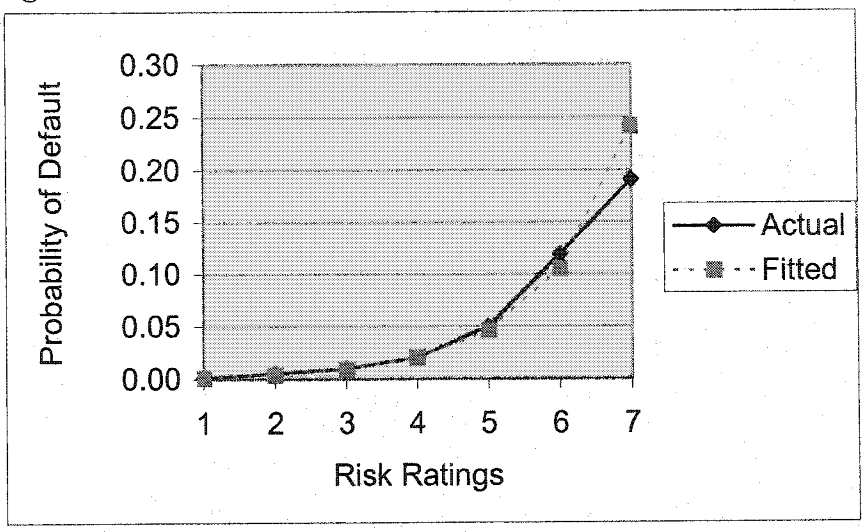
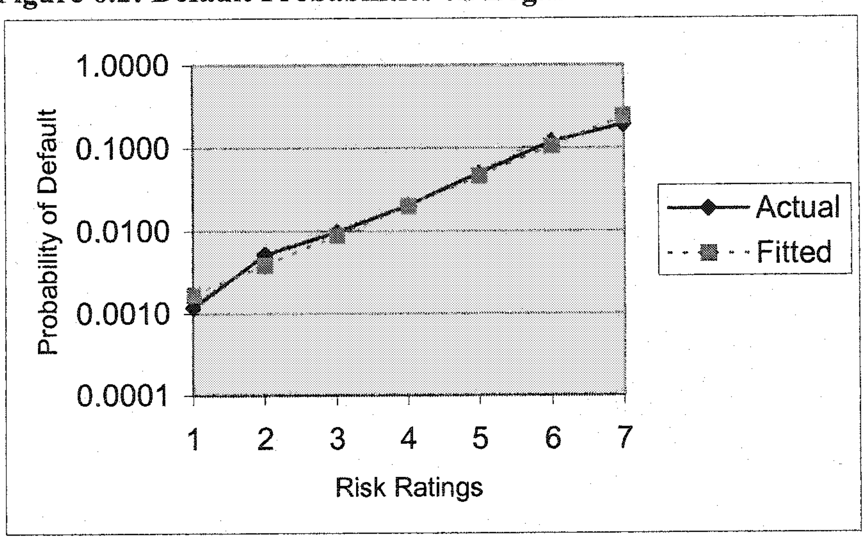


Figure 6.2: Default Probabilities on Logarithmic Scale



Non-rated customers have average default probability of 0.983%, which is very close to the probability of default of customers rated 3 (PD = 0.974%). This confirms the assumption that non-rated customers can be assigned risk rating 3. Average PD of nonrisk rated customers (0.983%) is lower than average PD of risk rated customers (1.529%), which confirms the earlier statement that non-rated customers represent lower risk because their income is supplemented with off-farm sources. Non-rated customers represent about half of all the customers in the database, but only a small percentage of total loan volume.

Customers in risk ratings 8 and 9 are assigned default probability of 100% because all customers in these risk ratings are in default.

6.3.3 Volatility of Default Probabilities

Volatility of default probability is the standard deviation of default probability. It is an input for the model that is not required by the IRB approach in the New Capital Accord, but it can be calculated based on annual default probabilities that are required by the Accord. CreditRisk+ technical document states that volatilities of default probabilities can be inferred directly by calculating the standard deviation of the time series of historical default probabilities for each rating grade (CSFP). See Column 3 of **Table 6.2** for historical standard deviations of default rates. The values are consistent with the observation that the standard deviation of default probability is 70-100% of default probability based on the experience of U.S. corporations (Wilde, 2000, p. 613). Standard deviation of default probabilities among farm real estate loans of the Farm Credit Bank of Texas in 1973-1992 is also about 100% of the mean (Barry, Sherrick, Ellinger, and Banner, Table 2).

Standard deviations of default probabilities are modeled as a function of risk ratings like default probabilities. The solid lines on **Figures 6.3** and **6.4** illustrate the historical standard deviations of default probabilities on linear and logarithmic scale. They are calculated as the standard deviations of the time series of historical default probabilities for each risk rating. Standard deviations increase exponentially with risk ratings, similar to default probabilities. OLS regression where the response variable is the logarithm of PD standard deviations, and predictor is the risk ratings[32], is used to estimate the function:

$$Ln(StDevPD) = -7.422 + 0.753 * \text{Risk Rating}.$$

Fitted values of standard deviations (dashed lines on **Figure 6.3** and **Figure 6.4**) are shown in Column 4 of **Table 6.2**.

---

[32] There are no outliers, influential observations, or problems with heteroscedasticity. The regression has a very good fit as the table below shows.

Summary Output for Estimating St.Dev. Of PD as a Function of Risk Rating

Regression Statistics	
Multiple R	0.9768931
R Square	0.9543201
Adjusted R Square	0.9451841
Standard Error	0.3897833
Observations	7

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	15.87031305	15.870313	104.45736	0.000153961
Residual	5	0.759655065	0.151931		
Total	6	16.62996812			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
Intercept	-7.4224859	0.329427006	-22.531504	3.201E-06	-8.26930359	-6.5756682
X Variable 1	0.7528591	0.073662118	10.220439	0.000154	0.563504954	0.9422133

Figure 6.3: Standard Deviations of Default Probabilities on Linear Scale

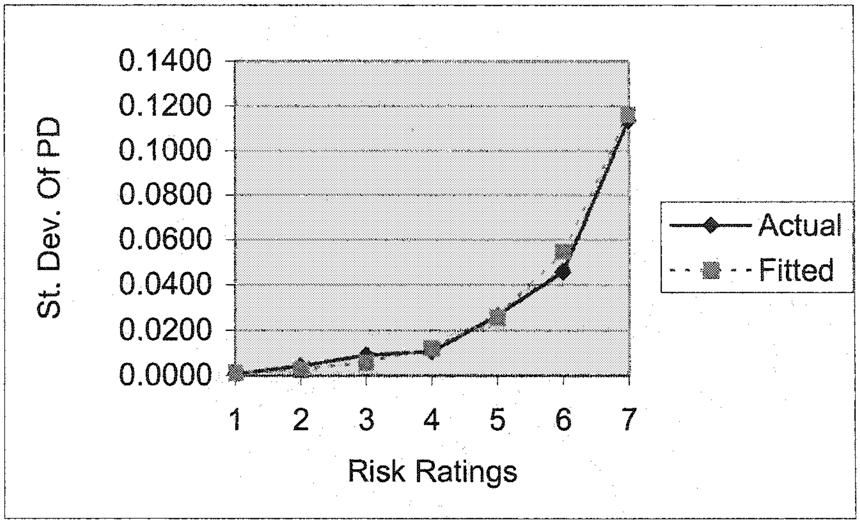
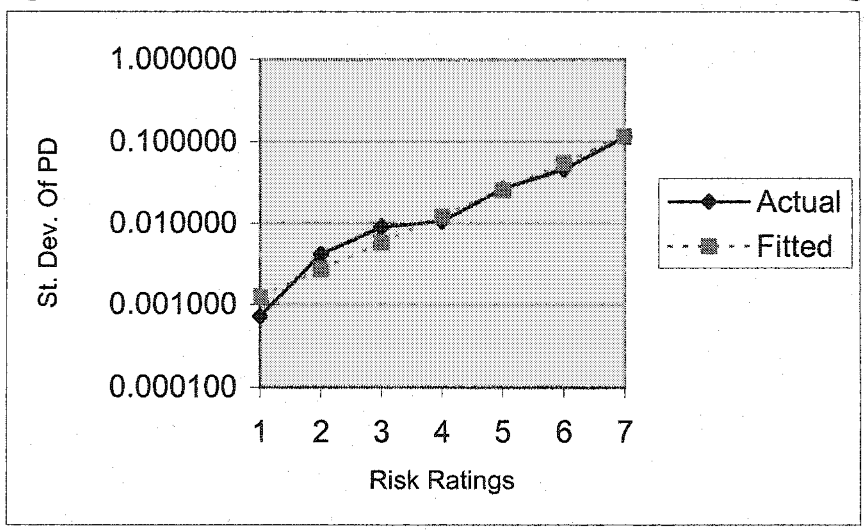


Figure 6.4: Standard Deviations of Default Probabilities on Logarithmic Scale



Standard deviations are also rounded to make them more readable for the users. Borrowers in risk ratings 8 and 9 are assigned zero volatility since their probability of default is deterministic and equal to one.

The CreditRisk+ model estimates sector volatilities of default probabilities as sums of volatilities of default probabilities of borrowers belonging to the sector. Sector volatilities can be entered directly into the model. To study the effect of using sector volatilities of default probabilities rather than approximating them by volatilities of the borrowers in the sectors, sector default probabilities are calculated for each industry in 1998-2002 (shown in **Table A.2** of Appendix A). Standard deviations of sector default probabilities are calculated based on the time series of historical default probabilities for each industry. Mean default probabilities per industry and their volatilities are given in **Table 6.3**.

Table 6.3: Default Probabilities and Their Volatilities by Industry

Industry	PD	St. Dev. Of PD
Crops	0.901%	0.339%
General Farms	2.035%	1.982%
Dairy	1.132%	0.416%
Swine	1.437%	0.555%
Other Livestock	1.545%	0.785%
Landlord	0.598%	0.190%
Rural Residence	1.412%	1.219%
Others	1.442%	1.202%
Total	1.182%	0.380%

The fact that standard deviations of default probabilities are estimated based only on the last five years potentially underestimates volatilities of default probabilities, since default probabilities increase several times during recessions. For example, the average default probability among farm real estate loans of the Farm Credit Bank of Texas in 1973-1992 was 1%, with the highest default probability of 3.78% in 1985 (Barry, Sherrick, Ellinger, and Banner, Table 2). The results based only on several years of data should be complemented by stress-testing (covered in Section 7.7).

6.3.4 Accounting for Risk Migration

There is an ongoing debate about what the risk ratings should represent: a "point-in-time" estimate or "through-the-cycle" estimate of borrower creditworthiness. The Basel paradigm of point-in-time risk rating assumes that theoretically, a default probability over time shows no variability. According to the point-in-time rating process, risk rating changes as the borrower's condition changes through the business cycle. The through-the-cycle risk rating represents credit strength under normal economic conditions. Through-the-cycle risk ratings have variability showing how default probabilities change during an economic cycle. Through-the-cycle risk ratings are used by major rating agencies such as Moody's or Standard & Poor's, and by the CreditRisk+ model. Risk migrations under the point-in-time paradigm are more common than under the through-the-cycle paradigm since risk ratings migrate to a higher or lower level depending on the economic conditions. The question whether internal risk ratings should represent long-term default probabilities or change through the cycle is at the heart of debate over the Basel's IRB approach (Blochwitz and Hohl). Both approaches have their disadvantages: the point-in-time approach makes risk ratings (and, therefore, capital requirements) sensitive to the level of economic activity. Thus, there is a danger of a sharp rise of capital requirements in recessions due to a large number of borrower downgrades and defaults. Through-the-cycle estimates lead to smoother capital requirements, but may underestimate risk (Blochwitz and Hohl) and they may also introduce vagueness into the estimates[33] (Rowe, March 2003). AgStar's risk ratings can be considered a hybrid between the through-the-cycle and point-in-time approaches. There is some migration, as risk ratings are updated when loans are renewed, or when new information about borrowers becomes available. However, AgStar's risk ratings are not based on point-in-time estimates like stock prices since many of them are updated

[33] "It is rather like saying that seasonally adjusted temperature in Minnesota in both January and July is zero degrees Celsius. It may be true, but it doesn't provide much information on what to wear when you go outside." (Rowe, May 2003, p. 85).

annually or even less frequently. They behave more like Moody's and Standard & Poor's ratings, showing significant volatility of default probabilities. To reconcile the two paradigms, the effect of risk migrations is included into the estimates of default probabilities and their volatilities.

Table 6.4: 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[34] (see **Table 6.4**). 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. Thus, 89% of customers risk rated 1 in the beginning of the year remain in risk rating 1 by the end of the year, and 6% of customers risk rated 1 in the beginning of the year move to risk rating 2 by the end of the year. Some borrowers migrate to better grades, while others migrate to lower grades. Over time, migration to lower grades is more common than migration to higher grades since good loans pay off faster than bad loans (Wilberding, 2000). Defaulted customers usually stay in the defaulted state (risk ratings 8 and 9) and do not migrate to other risk ratings. Only the customers that are not in default both in the beginning and the end of

[34] For an example of a query used to generate this table, see **Query B.3** in Appendix B that selects ending risk ratings in 2002 for clients with beginning risk rating 1 in 2001.

year are included in the migrations. Defaulted customers are already accounted for in the calculations of default probabilities 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 6.2**) weighted by the percentages of clients in the risk ratings at the end of the period (**Table 6.4**). 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%. Volatilities of default probabilities are adjusted in the same way.

Table 6.5: 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 6.5**). Rounded default probabilities and their deviations are used as an input for the model.

6.4 Loss Given Default

In the model, recovery rates are considered to be constant, and exposures net of recoveries are used for the calculation of losses. Loss given default (LGD) is a defined as a percentage of exposure lost in the event of default. It is equal to one minus the recovery rate. The product of exposure at default and loss given default, (EAD*LGD), enters the model as net exposure. LGD must be assigned to every loan or lease in the portfolio.

The first step in determining loss given default is defining loss in the event of default. According to the New Basel Capital Accord, "The definition of loss used in estimating LGD is economic loss. This should include discount effects, funding costs, and direct and indirect costs associated with collecting on the instrument in the determination of loss" (p.61). Thus, LGD should include charge-offs on the principal and interest amount, legal fees, staff costs, and collection fees. Plus, LGD should include the "opportunity cost" of principal plus interest at the date of default less the present value of subsequent cash flows. LGD is difficult to estimate because it includes many different costs, and some of them (such as workout expenses and carrying costs) are hard to quantify. Also, agricultural lenders usually have a limited number of write-offs because they prefer workout arrangements such as restructuring or other workout arrangements in case of default because of their traditional personalized nature. Charge-offs represent known loss, while it may take several years to resolve a defaulted loan. The AgStar database contains unresolved loans that defaulted in the 1980s. Collateral illiquidity and the length of the litigation process can make the collection process lengthy.

The same problems on determining LGD are present in commercial lending. According to Moody's Investor Service, "There is no good framework for predicting the outcome of default. This deficiency is so poignant because default outcomes are so broadly diverse. A defaulted loan might pay off essentially in full with accrued interest or it might pay off only 5 cents on the dollar. A resolution might be complete by the next month or it might take 4½ years." (p. 8). Studies on LGD in commercial lending are rather inconclusive (Ong, p. 105). On average, LGD is 50% for unsecured and 35% for secured corporate bonds. Bond default recovery data may not apply to bank loans unless it has been adjusted for differences in collateral, industry segment, seniority, and so forth (Caouette et al.).

The foundation IRB approach of the New Basel Capital Accord recommends 50% LGD for corporate loans with unsecured claims and non-recognized collateral for senior claims, and 75% for subordinate claims. In the case of commercial or residential real estate used as collateral, LGD depends on the ratio of current collateral value (C) to the nominal exposure (E). If $C/E \leq 30\%$ then $LGD = 50\%$. If $C/E \geq 140\%$ then $LGD = 40\%$. If C/E is between 30% and 140% then LGD varies between 50% and 40% according to formula $\{1-[0.2 \times (C/E)/140\%]\} \times 50\%$. In the case of financial collateral, its value if adjusted for "haircut", and exposure is reduced for the part secured by financial collateral. (Basel Committee for Banking Supervision, 2001, paragraphs 195 – 221). Haircuts denoted H are discounts applied to the market value of collateral to protect against price volatility: H_E is designed to reflect the volatility of exposure, and H_C is designed to reflect the volatility of collateral. The adjusted value after haircut of the collateral (C_A) is $C_A = C / (1+ H_C + H_E)$. Banks can calculate H using their own estimates of market price volatility according to the 1996 Market Risk Amendment (Basel Committee for Banking Supervision, 1996(a)) assuming a 10-business-day holding period, a 99% confidence interval, and daily marking-to-market and remargining. Collateral must be marked-to-market and revalued within a minimum frequency of six months (§106). Collateral in agricultural lending is generally not revalued every six months, which makes it problematic to estimate volatility of collateral.

Under the advanced IRB approach, banks can use their own estimates of LGD. LGD of the exposure is equal to the internal estimate of LGD associated with the LGD grade to which the exposure is assigned (§222-224). Banks must provide several distinct LGD grades that are linked to product, borrower, or transaction types. In assigning an exposure to an LGD grade, transaction and collateral types should be taken into account (§324-345). The minimum requirement for the estimation of LGD under the advanced approach is using 7 years of internal data (§324-365), which cannot be fulfilled with currently available AgStar data. The other requirement is "Estimates of LGD must have a cautious bias. … Where only limited data is available, underwriting or collateral management standards have changed or where estimates of LGD for certain transaction types are known to be volatile, this bias needs to be more conservative. … If a positive correlation can reasonably be expected between the frequency of observed defaults and the severity of LGD, the estimate should be adjusted with a conservative bias. Additionally, if there are any residual risks that are not reflected in the bank's data or LGD estimates, the bank's estimates must be adjusted accordingly with a conservative bias." (§343).

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 6.6**). 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 6.6: 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 (see Chapter 3.3 for details). 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.

Net Realizable Values (NRV) of collateral are used in calculating the ratios of loan to collateral values to reflect collateral illiquidity and collection costs. First, Estimated Market Values (EMV) of collateral are used to adjust appraisal real estate values to account for inflation or deflation of collateral values since the date of appraisal (AgStar Financial Services, 2001). NRV is the net proceeds of collateral in case it is necessary to liquidate the loan by selling the security. Four discount percentages are available for input to discount EMV to NRV: 1) Market Value Adjustment Percent (the discount is applied when some length of time will elapse before the collateral could be sold and changes in the real estate market need to be provided for); 2) Acquisition Costs Percent (to provide for attorney fees, court costs, litigation costs, foreclosure costs, etc., in connection with acquisition of the collateral); 3) Own/Sell Costs Percent ("holding and selling" costs accounting for maintenance costs, taxes, insurance, utilities, realtor commissions, advertising, title and closing costs associated with owning and marketing the collateral); 4) Distressed Sale Costs Percent (discount the lender must incur to sell the collateral in a reasonable time period). These four discounts are added together and the sum is multiplied against the EMV to calculate NRV.

6.5 Sector Analysis

The New Basel Capital Accord is based on the idea of a one-factor credit risk model. The single systematic factor can be considered the overall macroeconomic factor that drives default probabilities of all loans. All borrowers are assigned to this sector, assuming uniform 20% asset return correlation between loans in the whole portfolio. One-factor credit risk model is used to set the IRB risk weights. The benefits of this assumption are the following: 1) Parameterization issues for default correlations are avoided; 2) One-factor models give rise to additive capital requirements, so the risk weights are valid for any portfolio; 3) This assumption is consistent with the Basel preference for conservatism. The drawback of this assumption is ignoring diversification and concentration effects in a portfolio[35]. The model in this study can overcome this disadvantage, but at the cost of requiring an additional input – default correlations between industries.

CreditRisk+ documentation states that the most straightforward application of CreditRisk+ is the one where all obligors are allocated to a single sector. This generates a conservative estimate of extreme losses. It does not provide any guidelines on how to identify different sectors. Therefore, implementations of the model are often based on a single generic sector. This approach is deemed acceptable for regionally concentrated portfolios (Boegelein et. al.).

The one-sector approach is considered as one of the scenarios in this study. The assumption that all borrowers belong to the same sector can be explained by the presence of factors (such as land values, interest rates, inflation, unemployment rate) that affect all

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[35] "The single factor assumption, in effect, imposes a single monolithic business cycle on all obligors. A revised Basel Accord must apply to the largest international banks, so the single risk factor should in principle represent the global business cycle. By assumption, all other credit risk is strictly idiosyncratic to the obligor. In reality, the global business cycle is a composite of a multiplicity of cycles tied to geography (e.g., political shifts, natural disasters) or to prices of production inputs (e.g., oil, commodities). A single factor model cannot capture any clustering of firm defaults due to common sensitivity to these smaller-scale components of the global business cycle. Holding fixed the state of the global economy, a local recession in, for example, Spain, is permitted to contribute nothing to the default rate of Spanish obligors. If there are indeed pockets of risk, then calibrating a single factor model to a broadly diversified international credit index may significantly understate the capital needed to support a regional or specialized lender." (Gordy, 2001, p. 23).

agricultural borrowers in a similar way. This approach is consistent with the conservative ideas of one sector in the New Capital Accord and CreditRisk+ documentation.

The main results of the model are derived under the assumption that borrowers belong to different sectors. 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. AgStar has identified over a hundred enterprise codes grouped into several major product categories (AgStar Financial Services, ACA, 2001). Most of the enterprise codes and product categories are the same across FCS associations. Consistent with AgStar internal practices and to insure that there is an adequate number of borrowers in each industry to estimate default probabilities per industry, customers are assigned to the following industries in the study:

- Crops (mostly corn and soybeans)
- General farms, primarily crop (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)

Table 6.7: 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

Correlations between industry default probabilities are estimated based on AgStar's historical data on default probabilities per industry over 1998-2002 (see **Table 6.7**). They are calculated as mean annual default probabilities per industry shown in **Table A.2** of Appendix A.

Based on the correlation structure, there appear 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.

It may be strange to see positive correlation between crops and livestock industries, since crops are an input for the livestock industry. When prices on crop commodities decrease, livestock producers benefit. External historical data shows that there is negative correlation between income in crop and livestock industries[36]. However, correlations of default probabilities are different from correlations in income. Default probability is usually represented by the term debt coverage ratio[37], a popular indicator of repayment capacity. There is positive correlation in term debt coverage ratio between crop and livestock industries, as confirmed by an outside data source (**Table 6.8**). The values are based on 1993-2001 farm data for Southern Minnesota.

Table 6.8: Correlation of Term Debt Coverage Ratio between Industries

	Crop	Dairy	Swine	OtherLvst
Crops	1.00	0.72	0.47	0.66
Dairy	0.72	1.00	0.36	0.44
Swine	0.47	0.36	1.00	0.24
OtherLvst	0.66	0.44	0.24	1.00

Source: www.finbin.umn.edu.

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

Table 6.9: 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

[36] USDA data at http://ers.usda.gov/data/costsandreturns/testpick.htm shows negative correlation between various crop and livestock industries in gross revenue less cash expenses excluding government payments (in dollars per planted acre, dollars per cwt, dollars per bred cow).

Southwestern Minnesota Farm Business Management Association data (www.finbin.umn.edu) shows negative correlation of net income ratio between crop and livestock industries.

[37] Term debt coverage ratio is equal to net farm operating income plus net non-farm income plus interest on term debt minus family living expenses and taxes, all divided by scheduled principal payments on term debt. Term debt coverage ratio tells whether a borrower produced enough cash to cover all (both farm and non-farm) intermediate and long-term debt payments.

requirements. Replacing negative correlations with zeros and rounding AgStar's internal correlation data, the correlations in **Table 6.9** are obtained. This correlation structure is used in the study.

6.6 Market and Operational Risks

Credit risk model is designed to estimate the amount of capital necessary to support credit risk, which is the major risk to an association. There are estimates that credit risk comprises about 90% of all the risks in the Farm Credit System. However, economic capital must account for all the risks, including market and operational risk. Market and operational risk capital requirements can be estimated through special models similar to credit risk models. Alternatively, when the Farm Credit Systems develops regulations for estimating market and operational risk capital in agricultural lending, the amounts of regulatory capital for operational and market risk can be used instead.

Operational risk is nearly impossible to quantify. A common approach to this problem is to acknowledge operating risk by adding a safety margin to the credit risk capital estimate, or to assume that the difference between economic capital and existing capital is due to unmeasured operating risk. The FCA recommends considering off-balance-sheet risk arising from asset/liability management transactions, wire transfer activity, pending or potential litigation, joint and several liability in estimating operational risk, but does not have any guidelines for quantifying operational risk (FCA). 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 for Banking Supervision, 2001, p.94). Annual gross income based on AgStar's 2002 Annual Report is about $158,401,300, which makes operational risk capital to be 0.87% of the gross exposure.

Market risk is defined as the risk of losses in the on-balance sheet and off-balance sheet positions arising from movements in market prices. The risks subject to the Basel requirements are the risks pertaining to interest rate related instruments and equities in the trading book, and foreign exchange risk and commodity price risk throughout the bank (Basel Committee for Banking Supervision, 1996(a)). 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. Associations are protected from the interest rate risk since they borrow funds from AgriBank to fund its lending operations in accordance with the Farm Credit Act (AgStar Financial Services, 2002). This leads to the assumption of minimal market risk capital. 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.

6.7 Summary of Model Parameterization Procedures

The data was received from AgStar in Microsoft Access® format. First, Access was queried to generate a list of the attributes for each loan and lease in the portfolio. These are reported in **Table 6.10**. Loan volume is calculated on a loan participation basis, where master agreements are combined into single loans as described in Section 6.2.

Table 6.10: AgStar Loan Attributes on December 31, 2002

General Information	Loan number Customer identification number (CIF) Loan type Customer involvement Cost center Branch office number Agricultural business code
Default Status	Accrual code Charge-off year-to-date Bankruptcy/foreclosure code Past due days Restructured index
Exposure at Default Characteristics	Volume Unfunded balance Participation basis
Risk Rating Characteristics	Customer risk rating Loan risk rating Credit score
Loss Given Default Characteristics	Net realizable value of collateral Guarantee index

The list of loan attributes is transferred in Excel. A short program is written in Visual Basic to generate several additional characteristics using the available loan attributes. First, a default status is assigned to the loans that satisfy the definition of default based on the loan accrual code, year-to-date charge-offs, bankruptcy/foreclosure code, past due days, and the index of restructured loans. Second, loan volumes, unfunded loan balances, and net realizable values of collateral are adjusted for participation percentages as described in Section 6.2. Third, risk ratings are assigned based on borrower risk rating, loan risk rating, and credit score using the procedure described in Section 6.3.1. Fourth, loss given default ratings are assigned based on the net realizable value of collateral, guarantee index, and loan type using the procedure described in

Section 6.4. Fifth, each loan is assigned to one of the industries as defined in Section 6.5 based on the agricultural business code.

To estimate default probabilities, Access is used to generate the number of defaulted and total customers for each year and each risk rating, as described in Section 6.3.2. This data is transferred to Excel, where mean default probabilities and their standard deviations are calculated for each risk rating. Default probabilities and their standard deviations are smoothed in Excel based on exponential functions. Access is used to generate risk migrations for each year and each risk rating. The risk migration data is transferred in Excel, where average risk migrations over the five years are calculated, and their effects are included in the calculations of default probabilities and their standard deviations.

Access is used to select the number of defaulted and total customers in each industry for each year. This procedure is identical to generating the number of defaulted and total customers for each risk-rating category. Default rates for each year and each industry are transferred to Excel, which is used to calculate mean default probabilities for each industry and correlations of default probabilities between the industries.

CHAPTER 7
MODEL RESULTS

This chapter describes model results and discusses their implications for loan portfolio management. Model outputs are expected and unexpected losses for the whole portfolio, individual loans and portfolio segments. They are used to determine capital adequacy, monitor portfolio risk, analyze concentrations, manage portfolio, conduct RAROC analysis and stress-testing.

7.1 Loan Loss Distribution

The main result of the credit risk model is the loan loss distribution (pictured on **Figure 7.1**). All model outputs are based on the loan loss distribution. Total risk funds are equal to the selected upper tail percentile of the distribution. Allowance is equal to the expected losses, or the mean of the distribution. Economic capital is the total risk funds less the allowance for loan loss.

Figure 7.1: Resulting Loan Loss Distribution

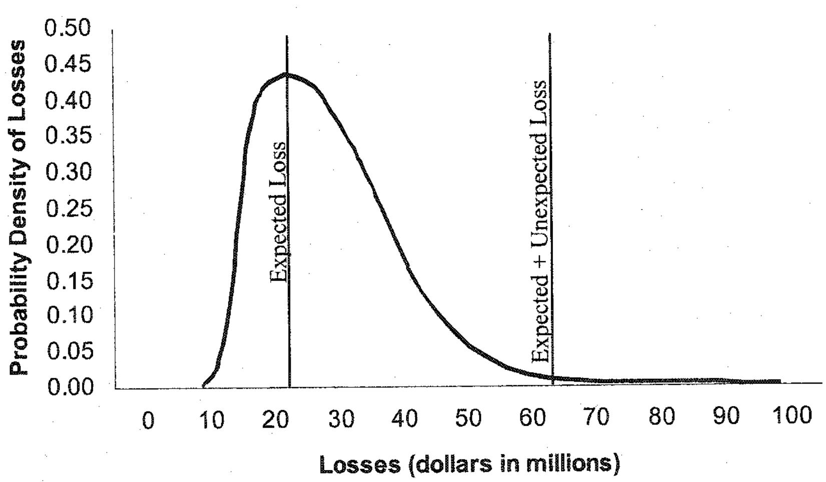


Table 7.1 shows the summary of the analyzed portfolio and the summary of the resulting loan loss distribution. Throughout the study, all exposures, losses, and percentiles are given in dollar amounts.

Table 7.1: Loan Loss Distribution Summary[38]

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

The loan loss distribution curve is derived based on 28,330 non-defaulted loans. The 332 defaulted loans shift the distribution along the x-axis to the right. Total exposure is the sum of individual exposures, which include unfunded commitments weighted at 75%. Maximum loss is the sum of exposures multiplied by Loss Given Default rates. Tail percentiles show the Value-at-Risk, which is the total required risk funds to cover expected losses and unexpected losses at selected confidence levels.

Skewness and kurtosis describe the shape of the loans loss distribution, skewed to the right with a long fat tail, reflecting the fact that large losses can happen, although with small probabilities.

[38] Total exposure is not equal to Total Loans in AgStar 2002 Annual Report. Total loans in the Annual Report do not include unfunded commitments but include other assets such as notes receivable, sales contracts, etc. in addition to loans and leases, and exclude any participations sold, acquired property, and accounts receivable.

Skewness shows the symmetry of a distribution around the mean. Skewness of a normal distribution is zero. Positive skewness in this case (1.11) means that the distribution has a longer tail on the right side of the distribution.

Kurtosis shows the probability density in the tails, whether they are flat or peaked compared to the normal distribution. Standard normal distribution has kurtosis equal to three, compared to the kurtosis of 4.80 in this resulting distribution. Distributions with kurtosis greater than three are said to have leptokurtosis, or "fat tails". A distribution with a fatter tail will have larger Value-at-Risk for a given percentile.

7.2 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 against capital 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 7.2**.

Table 7.2: Allowance

Expected Losses		% Exposure
On nondefaulted loans	12,781,624	0.49%
+On 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 actual 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 reported in **Table 7.2**.

The loan loss distribution allows for the comparison of economic capital at various confidence levels to the existing risk funds (**Table 7.3**). 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 99.50th percentile in deriving the regulatory function. The 99.97th 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 7.3: 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%

Table 7.3 (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 7.3** 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%. Still, the economic capital as a percent of risk-weighted assets is only about 3%, compared with the regulatory ratio of 7% and the actual permanent capital ratio of 12%.

Table 7.4: 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	

Table 7.4 shows the comparison of economic capital to the book capital under the 99.97th 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.

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)

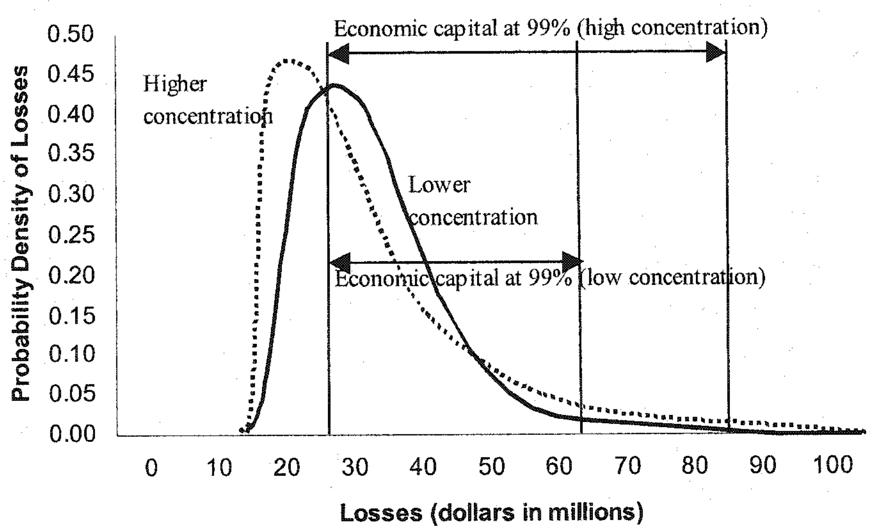
Under selected parameters, AgStar holds more than three times as much capital as the model requires. One may think that AgStar holds excessive economic capital, and it should reduce its book capital to the 7% permanent capital ratio. It is important to remember that probabilities of default and their 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 in Section 7.7) 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[39].

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

7.3 Portfolio Monitoring and Measuring Concentrations

Economic capital requirements reflect changing risk of the portfolio. Increasing risk can be defined in terms of the shift in the loan loss distribution. A deterioration of credit quality increases both the mean and the tail percentiles, shifting them to the right. An increase in concentration leaves the mean the same, but increases tail percentiles, making the tail fatter and longer (**Figure 7.2**). Thus, the model can be used to measure and monitor changes in both credit quality and concentrations in the portfolio.

Figure 7.2: Effect of Concentration on Loan Loss Distribution



Value-at-Risk as a percent of loan volume can be compared for the loan portfolio over time, showing changes in portfolio risk over several time periods. Lenders can analyze monthly, quarterly and annual trends in credit risk. To identify the portfolio segments that are responsible for most changes in portfolio risk, the differences in economic capital requirements per industry, loan type, client participation, etc. can be tracked over time. If undesirable concentrations increase over time, measures need to be taken to prevent further increases in concentration.

Economic capital requirements can be used to monitor the effect of projected portfolio growth for the upcoming year. For example, portfolio growth by $120 million (less than 5% increase in loan volume) can be achieved through adding a different number of loans to the portfolio. **Table 7.5** shows the effect of adding a different number of loans totaling $120 million to the portfolio. All loans have risk rating 3, LGD rating 3, industry crops.

Table 7.5: Effect of Adding Volume via Different Number of Loans

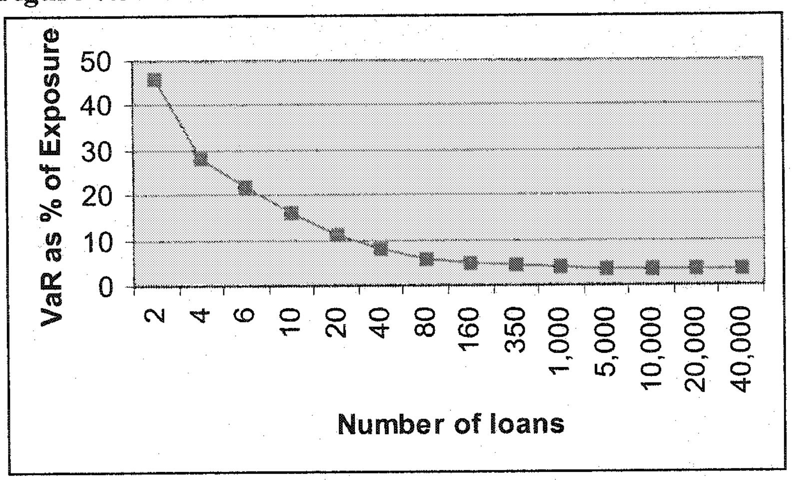
No. of Loans	% Increase VaR
1	96.20%
2	41.90%
3	24.50%
4	16.97%
6	10.88%
12	6.75%
60	4.67%
120	4.47%

When the growth is achieved via adding one $120 million loan, Value-at-Risk almost doubles. When the growth is achieved via adding sixty $2 million loans, Value-at-Risk increases by less than 5%. The mean of the distribution is the same in both cases, but the portfolio with lower diversification requires more capital. In a less diversified portfolio, the tail is longer, and more capital is necessary to support it.

This result is consistent with the Modern Portfolio Theory, which states that if investors have large single investments, they can reduce non-systematic risks without reducing returns if they divide their capital among multiple risks. Lenders can use loan participations to reduce their exposure on large loans.

Non-systematic (borrower-specific) risk in a portfolio is significant when there are large single loans and when the total number of loans in a portfolio is small. Next, the effect of changes in the number of loans on model results is explored. Since all the loans are different in AgStar's portfolio, it would be difficult to scale up or down the size of their portfolio. A loan with volume $1,000 in risk rating 3 and LGD rating 3 is replicated many times to study the effect of increasing number of loans on Value-at-Risk. **Figure 7.3** shows that Value-at-Risk as a percentage of exposure decreases rapidly when the number of loans is increased from 1 to about 300. This happens because diversification benefits from adding each new loan are large when the number of loans is small. Increasing the number of loans over about 300 loans does not decrease Value-at-Risk as a percentage of exposure much further, since there is already significant diversification in the portfolio.

Figure 7.3: Effect of the Number of Loans on VaR



The results show that concentration risk due to borrower-specific risk is significant when there are large single exposures or when there is a very small number of loans in a portfolio. The number of loans in a portfolio is not a concern for most FCS associations that have thousands of loans, but there is some concentration risk of single large loans, as shown later in the chapter **(Table 7.12)**.

Concentration due to unsystematic risk occurs when there are many loans in the same industry or when there is high correlation of default between industries. The loans in the same industry are assumed to be perfectly correlated due to common dependence on economic factors within one industry. Correlation of loans in different industries in the study is reflected by the correlation matrix (**Table 6.8**), where correlations between industries are less than 1, and several industries are independent. When all industries are independent under the current distribution of loans among industries, VaR decreases from $60,834,933 to $54,828,605. When all loans belong to the same industry, Credit Risk VaR at 99.97th percentile increases from $60,834,933 to $77,864,572. The allowance for loan loss remains unchanged. The assumption that all loans belong to the same industry has approximately the same effect on the results as assuming a correlation of 1.0 between all the industries. This assumption generates a conservative estimate of economic capital requirements when industry correlation structure is unknown.

7.4 Subportfolio Analysis

The model produces allowance and economic capital requirements for each portfolio segment, such as industry, loan type, risk rating, etc. Allowance and economic capital requirements for each segment is a sum of allowances and capital requirements for all loans in the given segment. Knowing segment allowance and economic capital requirements is useful in analyzing comparative risk of various segments and concentration risks. If a certain sector requires a lot of economic capital, concentration of loans in that sector should be carefully looked at.

Allocation of allowance and economic capital across various subportfolios allows one to see which segments represent most risk, and how allowance and economic capital requirements are distributed across the portfolio. **Table 7.6** shows the results of segmentation by industry. The table shows that there are concentrations in crops, dairy, and swine industries by volume, allowance requirements, and economic capital requirements. The "Landlords" segment is the least risky industry since it represents 6.1% of volume, but requires only 1.4% of allowance, and 2.8% of economic capital. "General Farms" and "Rural Residence" are also comparatively low risk industries, requiring small percentages of capital and allowance compared to their volumes. Clients in these industries have significant non-farm income that decreases the risk of default.

Table 7.6: Allowance and Economic Capital Requirements by Industry

Industry	Allowance($)	Allowance(%)	Volume(%)[40]	Capital($)	Capital(%)	Volume(%)[40]
Crops	3,590,030	15.49%	29.25%	15,101,118	23.69%	29.53%
Dairy	4,464,015	19.26%	14.75%	7,535,341	11.82%	14.52%
Swine	3,942,179	17.01%	16.26%	11,085,491	17.39%	16.32%
Other Livestock	772,560	3.33%	6.76%	3,472,904	5.45%	6.83%
Landlords	315,170	1.36%	6.11%	1,770,203	2.78%	6.11%
General Farms	512,267	2.21%	4.70%	1,680,901	2.64%	4.74%
Rural Residence	1,021,622	4.41%	2.39%	700,123	1.10%	2.27%
Others	8,562,751	36.94%	19.77%	22,391,687	35.13%	19.68%
Total	23,180,594	100.00%	100.00%	63,737,771	100.00%	100.00%

The "Others" segment represents only 20% of volume but requires almost twice the percentage of allowance and economic capital. To understand what causes the risk in this diverse segment, further analysis of this industry is conducted. **Table 7.7** shows the allowance and economics capital requirements for the several components of the "Other" industry identified consistently with AgStar's industry definitions and based on loan volume, allowance, and economic capital requirements. Industrial organic chemicals industry requires a significant amount of economic capital (13.29%), but represents only 5.07% in loan volume. This result implies that AgStar should closely monitor the

[40] In tables 7.6. through 7.11, Volume includes unfunded balances weighted at 75% and excludes volumes under $10. Percent volume for the purpose of comparison with percent of allowance requirements (column 4) includes defaulted loans, while percent volume for the purpose of comparison with percent economic capital (column 7) does not include defaulted loans.

performance of ethanol plants. The food products industry and the trade (wholesale and retail) industry also have above average capital requirements in the portfolio. The "unknown" and the "no major ag product" industries are quite risky, with the total of 5.2% of loan volume and 9.5% of economic capital. This result suggests that AgStar should improve its efforts in assigning borrower industries to be able to identify the source of risk in these categories.

Table 7.7: Allowance and Economic Capital Requirements for "Other" Industry

Industry	Allowance($)	Allowance(%)	Volume(%)[40]	Capital($)	Capital(%)	Volume(%)[40]
Chemicals	1,209,703	5.22%	4.99%	8,467,814	13.29%	5.07%
Food Products	1,057,502	4.56%	5.35%	5,041,809	7.91%	5.43%
Unknown	900,792	3.89%	3.10%	4,330,269	6.79%	3.15%
Trade	491,980	2.12%	1.95%	1,735,237	2.72%	1.96%
No Major Ag Product	510,803	2.20%	2.05%	1,740,445	2.73%	2.04%
Crop Prep Services	3,795,177	16.37%	0.29%	0	0.00%	0.00%
Others*	596,794	2.57%	2.04%	1,076,113	1.69%	2.03%
Total	8,562,751	36.94%	19.77%	22,391,687	35.13%	19.68%

Note: Others include agricultural services (soil preparation services, crop services, veterinary services, farm labor, landscape and horticulture services), forestry, lumber and wood products, farm machinery, trucking, land developers, and borrowers without a record in the "Borrower" table (because they were purchased from other lenders).

Analyzing allowance requirements across various segments of the "other" industry in **Table 7.7** shows that a large portion of allowance requirements is allocated to the "crop preparation services" industry (16.37% of allowance requirement), which represents only 0.29% of loan volume. This segments contains a large single defaulted loan.

Table 7.8: Allowance and Economic Capital Requirements by Loan Type

Loan Type	Allowance($)	Allowance(%)	Volume(%)[40]	Capital($)	Capital(%)	Volume(%)[40]
Operating	8,760,586	37.79%	24.98%	17,210,218	27.00%	24.95%
Intermediate Term	6,750,657	29.12%	21.09%	17,071,725	26.78%	21.10%
Real Estate	5,245,741	22.63%	43.74%	25,791,831	40.47%	43.92%
Country Living	1,622,314	7.00%	6.49%	2,060,241	3.23%	6.35%
Lease	801,239	3.46%	3.71%	1,603,270	2.52%	3.68%
Total	23,180,594	100.00%	100.00%	63,737,771	100.00%	100.00%

Table 7.8 shows that real estate and country living loans present less risk than operating and intermediate term loans. Similar to the segmentation by industry, segmentation by customer involvement in **Table 7.9** shows that landlords and rural residents are relatively low risk types of customer involvement. Processing and marketing business and the "other" involvements are relatively risky. Segmentation by industry, loan type, and customer involvement (**Tables 7.7, 7.8, 7.9**) confirms the fact that AgStar has a significant concentration in the segment of full-time farmers in crops, dairy, and swine industries with operating and intermediate-term loans, and it is a large source of risk in the portfolio.

Table 7.9: Allowance and Economic Capital Requirements by Customer Involvement

Involvement	Allowance($)	Allowance(%)	Volume(%)[40]	Capital($)	Capital(%)	Volume(%)[40]
Full Time	9,081,879	39.18%	25.71%	18,090,302	28.38%	25.69%
Part Time	6,062,020	26.15%	18.61%	11,854,125	18.60%	18.58%
Landlord	4,627,190	19.96%	41.52%	22,347,841	35.06%	41.67%
Non-farm residential	1,596,527	6.89%	6.43%	2,043,388	3.21%	6.30%
Farm related business	801,239	3.46%	3.71%	1,603,270	2.52%	3.68%
Processing & marketing business	714,546	3.08%	2.75%	5,579,656	8.75%	2.79%
Other	297,195	1.28%	1.27%	2,219,190	3.48%	1.29%
Total	23,180,594	100.00%	100.00%	63,737,771	100.00%	100.00%

Allocation of economic capital across segments can be used for setting risk-based credit limits to control concentration risk within certain industries and other portfolio segments. Concentration limits are useful in controlling extreme losses (beyond the desired confidence level). For example, AgStar may decide that no more than a certain percentage of economic capital should be allocated to the customers growing crops. Loans in excess of the limits may be candidates for sale or participation in derivative markets: "there are two basic alternatives for consideration: either sell loans and remove them from the sheet or retain the loans on the balance sheet but alter their default characteristics" (Pederson and Wilberding, p. 16).

Allowance and economic capital requirements across risk ratings and loss given default ratings (**Tables 7.10** and **7.11**) can be used to monitor and control the exposure to borrowers in certain ratings. For example, it can be calculated based on **Table 7.10** that loans of unacceptable quality (risk ratings 6, 7, and 8) represent 2.32% of non-defaulted loan volume and 5.14% of economic capital requirements. They also represent 3.62% of overall loan volume and require 46.90% of allowance. Defaulted but unresolved loans have high allowance requirements.

Table 7.10: Allowance and Economic Capital Requirements by Risk Rating

Risk Rating	Allowance($)	Allowance(%)	Volume(%)[40]	Capital($)	Capital(%)	Volume(%)[40]
1	238,429	1.03%	12.09%	3,592,382	5.64%	12.27%
2	786,737	3.39%	19.78%	7,382,833	11.58%	20.08%
3	4,238,669	18.29%	32.95%	22,482,391	35.27%	33.45%
4	5,552,834	23.95%	28.06%	23,641,035	37.09%	28.42%
5	1,493,044	6.44%	3.50%	3,366,916	5.28%	3.46%
6	638,385	2.75%	1.51%	1,445,855	2.27%	1.52%
7	10,091,853	43.54%	2.08%	1,826,359	2.87%	0.80%
8	140,642	0.61%	0.03%	0	0.00%	0.00%
Total	23,180,594	100.00%	100.00%	63,737,771	100.00%	100.00%

Volume distribution among different risk ratings can also be seen from **Table 7.10**. Thus, loans in risk rating 3 represent 32.95% of overall volume (column four), which exceeds the Basel II requirement of 30% maximum loan volume in any single risk rating. Volume distribution among the risk ratings shows that most of AgStar's loan volume is of acceptable quality.

Table 7.11: Allowance and Economic Capital Requirements by LGD Rating

LGD Rating	Allowance($)	Allowance(%)	Volume(%)[40]	Capital($)	Capital(%)	Volume(%)[40]
1	968,657	4.18%	36.57%	10,540,957	16.54%	36.62%
2	3,833,307	16.54%	15.82%	7,110,087	11.16%	15.65%
3	15,685,989	67.67%	39.26%	32,274,440	50.64%	39.26%
4	2,692,642	11.62%	8.34%	13,812,287	21.67%	8.47%
Total	23,180,594	100.00%	100.00%	63,737,771	100.00%	100.00%

Average allowance/economic capital requirements per dollar of volume in each risk rating/LGD rating/industry/etc. can be obtained by dividing the amount of allowance and economic capital by the volume in each subportfolio segment. This analysis produces more precise values of economic capital requirements for the risk ratings (since they account for portfolio effects and are based on the actual level of risk in the portfolio) than those currently used by AgStar (described in Chapter 3.2).

Allowances and economic capital requirements for subportfolios can be used in RORAC analysis to compare risk-adjusted profitability across various portfolio segments, as described in Chapter 7.6.

7.5 Portfolio Management

The model allows for analyzing the effects of any changes in the portfolio composition, such as excluding some of the existing loans or adding new loans. The effects depend on the characteristics of the analyzed loan(s) and the rest of the portfolio, including the correlation of the analyzed loans(s) with the rest of the portfolio.

The effect of adding and removing loans can be analyzed by comparing capital requirements before and after the change. Economic capital and allowance requirements for a group of loans is the difference in the portfolio allowance and economic capital before and after adding or eliminating a group of loans.

The effect of removing a loan or several loans can also be approximated by the risk contribution of the loans. Risk contribution is the incremental amount of economic capital to support the loan. The risk contribution of a loan depends on the size and loss given default of the loan, borrower's probability of default, and correlation with other loans. The sum of risk contributions of all loans is equal to the economic capital required for the whole portfolio.

A credit limit system can be developed based on having exposures with equal expected losses or risk contributions (CSFP, p. 29). Thus, individual credit limits can be based on levels that are inversely proportional to default probabilities of the borrowers.

Risk contributions are useful in determining what loans present most risk in a portfolio. A substantial part of portfolio risk can be managed by focusing on the riskiest loans. The riskiest loans can be identified after sorting all the loans according to their risk contributions.

Table 7.12 shows the top 10 loans with the largest risk contributions. Most of them are net of "master" and "sold" participations, grouped by customer number, loan type, and cost center.

Table 7.12: Top 10 Riskiest Loans

Expected Loss	Loan Risk Contribution	Loan Volume
276,919	3,088,500	24,615,000
154,223	1,473,629	13,708,679
297,472	911,678	2,379,772
107,834	785,432	9,585,255
127,405	753,244	7,549,936
101,390	704,137	13,518,616
121,191	690,102	7,181,661
98,377	667,629	8,744,606
156,386	619,790	5,957,576
93,353	593,232	8,298,045
88,245	537,077	11,766,065

To reduce credit risk, the riskiest exposures can be sold or required to provide larger collateral. Credit derivatives (described earlier) can be used to transfer the risk to another party while maintaining client relationship. The risky exposures should be monitored more closely to detect early deterioration of credit quality.

Table 7.13 shows that after excluding the 5 riskiest loans from the portfolio by selling or participations, volume decreases by only 2%, while economic capital requirement decreases 15%, and the allowance decreases by almost 8%. Thus, excluding only the five riskiest loans significantly decreases portfolio risk and capital requirements.

Table 7.13: Effect of Excluding 5 Riskiest Loans

	Before	After	% Decrease
Volume	2,608,343,079	2,550,504,437	2.22%
Credit Risk Capital at 99.97%	37,654,340	31,837,047	15.45%
Expected Defaults	12,781,624	11,817,772	7.54%

Similarly, the effect of removal of potential candidates for swapping or for sale can be analyzed to determine how their removal from the portfolio will change the level of risk in the portfolio. The previous Section 7.4 (Subportfolio Analysis) described how to identify concentrations in a portfolio. Once an undesirable concentration is detected, such as operating loans to full-time crop farmers, a lender may want to sell some of the loans from this segment to decrease concentration risk in the portfolio. Removing loans that have high probability of default would also reduce the overall risk in the portfolio.

Loan sales, purchases, participations, and credit derivatives are different ways allowing modifying portfolio composition to reach optimal risk, return, and capital adequacy. Comparing economic capital before and after the removal of loans, modifications of loss given default characteristics of loans, and addition of new loans shows how much it would affect the overall level of risk in the portfolio.

Analysis of the effect of adding new loans can be done before making large loans that considerably affect the existing portfolio. **Tables 7.14** and **7.15** show the difference between adding loans with the same volume, industry, and LGD rating, but different risk ratings. Both loans contribute 0.38% to portfolio volume. When the loan has risk rating

1, it adds only 0.12% to credit risk capital and 0.10% to expected loss, decreasing portfolio risk and economic capital as a percent of volume. A loan with risk rating 5 adds 2.47% to credit risk capital and 2.05% to expected loss, increasing portfolio risk.

Table 7.14: Effect of Adding a Loan with Volume $10,000,000, Risk Rating 5, LGD Rating 3, Industry Crops

	Before	After	% Increase
Volume	2,608,343,079	2,618,343,079	0.38%
Credit Risk Capital	37,654,340	38,586,244	2.47%
Expected Loss	12,781,624	13,044,124	2.05%

Table 7.15: Effect of Adding a Loan with Volume $10,000,000, Risk Rating 1, LGD Rating 3, Industry Crops

	Before	After	% Increase
Volume	2,608,343,079	2,618,343,079	0.38%
Credit Risk Capital	37,654,340	37,698,795	0.12%
Expected Loss	12,781,624	12,794,124	0.10%

Table 7.16: Effect of Adding a Loan with Volume $10,000,000, Risk Rating 1, LGD Rating 3, Industry Landlord

	Before	After	% Increase
Volume	2,608,343,079	2,618,343,079	0.38%
Credit Risk Capital	37,654,340	37,681,702	0.07%
Expected Loss	12,781,624	12,794,124	0.10%

Note: Credit Risk Capital is estimated at 99.97th percentile. Expected loss is loss on non-defaulted loans.

Tables 7.15 and **7.16** show the effects of adding a new $10,000,000 loan with risk rating 1 and loss given default rating 3 to different industries in the existing portfolio. Both loans have the same expected loss, but the loan to a landlord requires less economic capital than the loan to a crop grower. This happens because the landlord industry has less risk (smaller default probability and its volatility) than the crops industry (see **Table 6.2** for default probabilities and their volatilities per industry), and also less correlation with the rest of the loans in the portfolio than the crops industry. Column 4 of **Table 7.23**

shows risk contributions to a new loan with volume $10,000,000, risk rating 3 and LGD rating 3 by industry.

The risk contribution of a new loan depends on the correlations of the new loan's industry with other industries as well as on the correlation between all other industries, as shown in **Table 7.17**.

Table 7.17: Effect of Correlation of New Loan with Volume $10,000,000, Risk Rating 3, LGD Rating 3 with Other Loans.

	Risk Contribution of New Loan under	
Correlation of new loan with other industries	Existing correlation between other industries	Perfect correlation between other industries
100%	444,894	366,830
50%	264,180	157,362
0%	61,790	-61,675

The more correlated the new loan's industry is with other industries, the higher the new loan's risk contribution. If the new loan's industry is perfectly correlated with the other industries, the risk contribution of a new loan is seven times as much as it would be if the new loan's industry were independent of the other industries.

The correlation structure between the other industries also matters. If all other industries are perfectly correlated, adding a new loan to an industry uncorrelated with the other industries decreases total economic capital because it has a large diversification effect on the portfolio (bottom row, column 3 in **Table 7.17**). If the portfolio already has some diversification under the current correlation structure (given in **Table 6.8**), a new loan uncorrelated with other loans requires a positive amount of economic capital (bottom row, column 2 in **Table 7.17**).

7.6 RAROC Analysis

Allowance and economic capital requirements can be used in the Risk-Adjusted Return on Capital (RAROC) ratios. We define, RAROC = (Net Revenue – Expected Loss) / Economic Capital. In a nutshell, RAROC gives a lender an ability to apply the same measure to consistently compare business lines with different risks, estimate trade-offs between risks and returns, price loans on a risk-adjusted basis, and set hurdle rates that can be used to evaluate profitability of transactions across product lines. RAROC sits at the core of an organization affecting internal risk policies and strategic decisions, performance measurement, determination of compensation schemes and enhancement of shareholder value (Ong, p. 241). The major drivers for RAROC-based performance in commercial lending are investors and shareholders who seem to reward banks performing RAROC-based profitability and allocation disclosure (ERisk). Thus, a RAROC strategy based on economic capital is necessary for lenders to be competitive. Since a bank-wide RAROC capital allocation allows optimizing risks and returns, economic capital can be viewed as the best tool to find the optimal trade-off between the conflicting interests of shareholders (who are trying to avoid over-capitalization to optimize profitability) and FCA banks and regulators (who are trying to avoid under-capitalization due to the implied risk of insolvency).

RAROC analysis can be conducted at the portfolio level, the portfolio segment level, and the loan level. Portfolio economic capital and allowance can be used in the portfolio-level RAROC ratios to consistently measure the profitability of an association as a whole over time. Portfolio RAROC for 2002 is net income divided by economic capital. Net income for 2002 is $42,146,000 (AgStar Financial Services, 2002);

economic capital at 99.97^{th} confidence level is $63,737,771. This yields RAROC of 66%. Economic profit is net income minus a charge for the cost of capital, where the cost of capital is the required rate of return times the amount of economic capital. Assuming that cost of capital is 12% (following Pederson and Wilberding), economic profit for 2002 is $42,146,000 – 12% * $63,737,771 = $34,497,467. Risk-adjusted return on risk-adjusted capital, RARORAC, is equal to economic profit divided by economic capital, which is 54%.

Subportfolio economic capital and allowance can be used in analyzing subportfolio RAROC ratios to compare risk-adjusted returns of different portfolio segments. Individual risk contributions and expected losses can be used in RAROC ratios for individual loans. This measurement facilitates efficient utilization of capital and contributes to lender's profitability.

Estimation of the numerator in the RAROC ratio, net returns for loans and subportfolios, is outside the scope of the study. One may use the approach taken by Wilberding (1999), who lets a lender assign loan-level costs and returns based on loan size, loan type, and loan risk based on lender's knowledge and experience.

To quickly estimate approximate allowance and economic capital for small new loans, AgStar can use the tables below that show average allowances and economic capital requirements per $1 of exposure (**Tables 7.18** and **7.19**). These tables use the conservative assumptions that new loans are perfectly correlated with the rest of the loans in a portfolio. To estimate how much allowance/economic capital is needed for a new loan with a given risk rating and LGD rating in relationship to the given portfolio, the new loan volume should be multiplied by the percentage in the corresponding risk rating and LGD rating. For example, a loan with $10,000 volume, LGD rating 2 and risk rating 3 would require $10,000 * 0.300% = $30 of allowance, and $10,000 * 1.736% = $173.6 of economic capital. This information can be use to quickly estimate RAROC for small new loans for pricing purposes.

Table 7.18: Average Allowance per $1 of Exposure (by Risk Rating/LGD Rating)

Rating	1	2	3	4
1	0.008%	0.050%	0.125%	0.188%
2	0.015%	0.100%	0.250%	0.375%
3	0.045%	0.300%	0.750%	1.125%
4	0.068%	0.450%	1.125%	1.688%
5	0.157%	1.050%	2.625%	3.938%
6	0.300%	2.000%	5.000%	7.500%
7	0.750%	5.000%	12.500%	18.750%

Table 7.19: Average Capital per $1 of Exposure (by Risk Rating/LGD Rating)

Rating	1	2	3	4
1	1.018%	1.123%	1.307%	1.462%
2	1.037%	1.245%	1.615%	1.923%
3	1.110%	1.736%	2.844%	3.770%
4	1.165%	2.104%	3.766%	5.155%
5	1.386%	3.576%	7.453%	10.695%
6	1.735%	5.907%	13.291%	19.468%
7	2.838%	13.267%	31.728%	47.169%

The information for RAROC ratios can be provided in detail for large new loans that undergo more detailed consideration. The difference in the portfolio-level economic capital and allowance before and after adding a new loan are the amounts necessary to support a new loan.

Table 7.20: Allowance/Economic Capital Requirement for New Loan with Volume $10,000,000, LGD Rating 3, Industry Crop, Risk Ratings 1 and 5

		Before	After	New Loan
Risk Rating	Exposure	2,608,343,079	2,618,343,079	10,000,000
1	Ec. Capital ($)	63,737,771	63,782,226	44,455
	Allowance ($)	23,180,594	23,193,094	12,500
5	Ec. Capital ($)	63,737,771	64,669,675	931,904
	Allowance ($)	23,180,594	23,443,094	262,500

Table 7.20 shows allowance and economic capital requirements of a new loan to a crop grower with $10,000,000 of loan volume, an LGD rating 3, and risk ratings 1 and 5, respectively. As the probability of default increases 20 times from risk rating 1 to risk rating 5, economic capital and allowance also increase about 20 times.

In conducting RAROC analysis to make new loans and compare risk-adjusted profitability of various portfolio segments and loans, one must remember to consider not only economic capital, but also capital required by the regulator. "Ignoring regulatory capital requirements is like evaluating an investment decision but ignoring the relevant tax implications, in that both are only relevant in a world without government." (Falkenstein, p. 10). For example, required economic capital for high quality loans is usually very small (under 2%), while regulatory capital is still 7% until the New Basel Capital Accord gets adopted within the Farm Credit System. If there is a surplus of regulatory capital at the lending institution, it is appropriate to invest into such loans. However, if there is no regulatory capital surplus, the lender will require 7% in new capital to accommodate the loan, and the economic approach would underestimate required capital.

Capital is a function of either regulatory or economic capital depending on existing assets and liabilities on and off balance sheets (Falkenstein, p. 2). Falkenstein derives the following formula for determining the marginal capital for Project I:

$$\text{MarginalCapitalCost(I)} = \text{Max[RegCap(I)} - \text{SurplusRegCap, EconCap(I)} - \text{SurplusEconCap]}$$

where RegCap(I) and EconCap(I) reflect the marginal increase in required regulatory and economic capital for Project I, and

$$\text{SurplusRegCap} = \text{Max[BookCapital} - \text{Regulatory Required Capital, 0]}$$

$$\text{SurplusEconCap} = \text{Max[BookCapital} - \text{Economic Required Capital, 0]}$$

This formula implies that marginal required capital is a function of both regulatory and economic capital, while either regulatory or economic capital is the sole constraining factor.

Basically, if a lender is constrained by regulatory capital, it should use regulatory capital to evaluate the project's returns. If it is constrained by economic capital, it should use economic capital to evaluate the project's returns. Thus, determining which capital is binding is of primary importance for conducting optimal RAROC analysis of projects.

7.7 Stress-Testing

Stress-testing gauges potential vulnerability of financial institutions to exceptional but plausible events. Stress tests vary from determining the impact of one or more risk factors on a portfolio's value (sensitivity stress-tests) to simultaneous moves in a number of risk factors, for example, recovery rates and default probabilities (scenario stress-tests), reflecting an actual event that happened in the past or a hypothetical event that is possible in the future.

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).

Jones and Mingo (p. 58) state that stress-testing can at least partially compensate for the shortcomings in credit risk models. At present, there is no commonly accepted framework for verifying the accuracy of credit risk models. It is a Basel regulatory requirement to "back-test" internal market risk models based on 250 observations that have one-day time horizons (Basel Committee on Banking Supervision, 1996(b)). Back-testing gauges the quality and accuracy of models by comparing model-generated measures to actual outcomes. Credit risk models usually assume a one-year horizon, they have high target insolvency rates, and they are sensitive to credit cycles. Thus, an impractical number of years of loss data is necessary for adequate back-testing.

Some banks compare estimated credit losses to actual loss experiences. This addresses the model's ability to predict expected losses in a typical year, but it does not consider predictive ability of unexpected losses (Federal Reserve System Task Force on Internal Credit Risk Models, p.52).

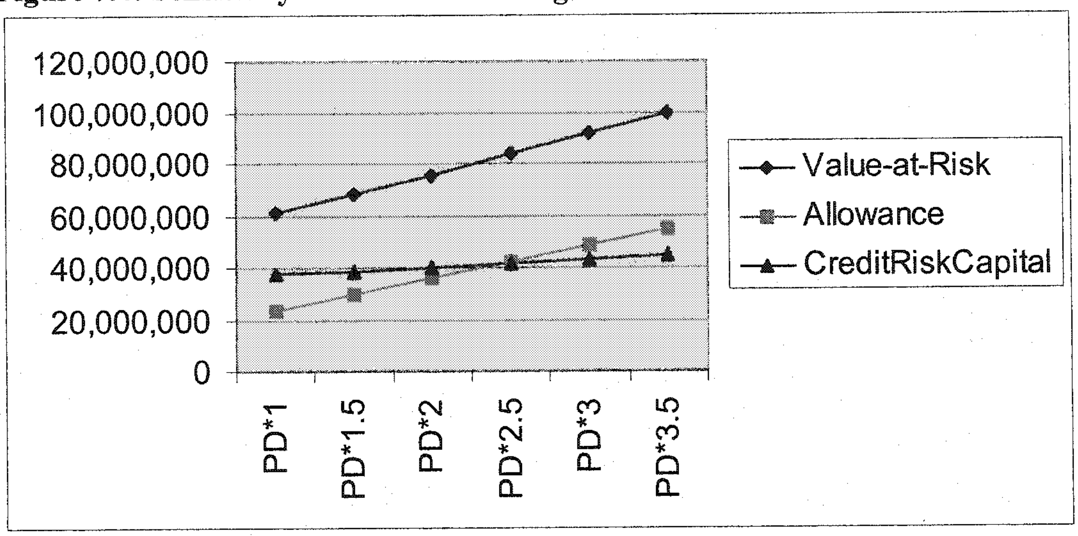
Stress-testing provides a good way of testing the models since there are not many important parameters in a credit risk model (Ong, p.236). In this chapter, sensitivity to changes in individual parameters (default probabilities and their volatilities, recovery rates, percentage of unfunded commitments, degree of correlation between industries) is covered first. Then sensitivity to different assumptions in the model is reviewed. Finally, multiple parameters are changed to extreme or historical values such as economic events of the 1980s to estimate the performance of the model under various scenarios.

7.7.1 Sensitivity to Individual Parameters

It is important to study model sensitivity to individual parameters to know which parameters are critical for the accuracy of the results. “Parameters must be shocked up and down to study how the model reacts to incorrect parameterization” (Ong, p.237).

To test the sensitivity of results to changes in default probabilities, all default probabilities are scaled up by 1.5; 2; 2.5; 3; 3.5 (**Figure 7.4**).

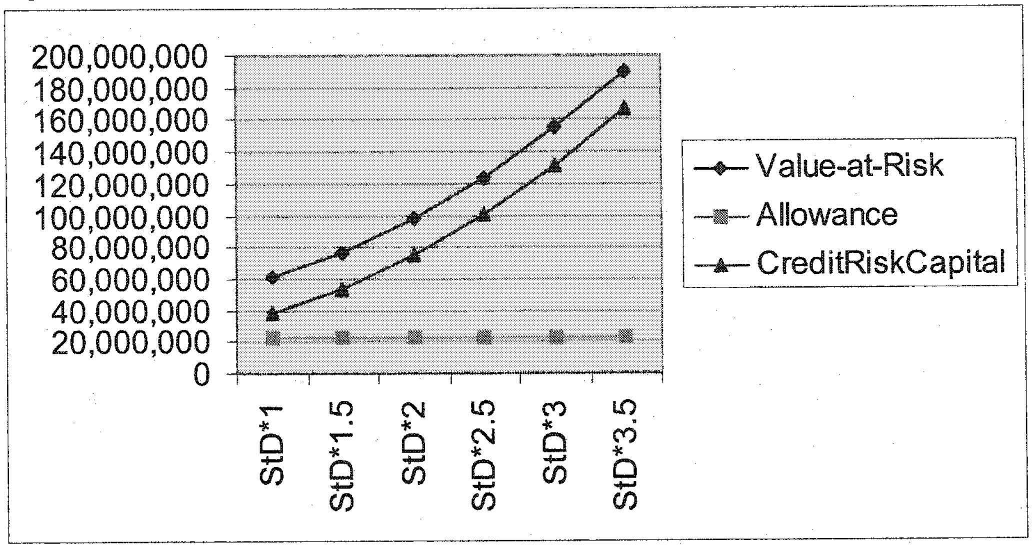
Figure 7.4: Sensitivity of Results to Changes in Default Probabilities



Under these multipliers, default probabilities do not exceed 100%. The multipliers are consistent with default history in U.S. commercial lending, which shows that default probabilities can double or triple between the high and low points of a credit cycle. Value-at-Risk increases linearly with increase in default probabilities, but most of this increase is attributed to increase in allowance. Credit risk capital stays almost constant.

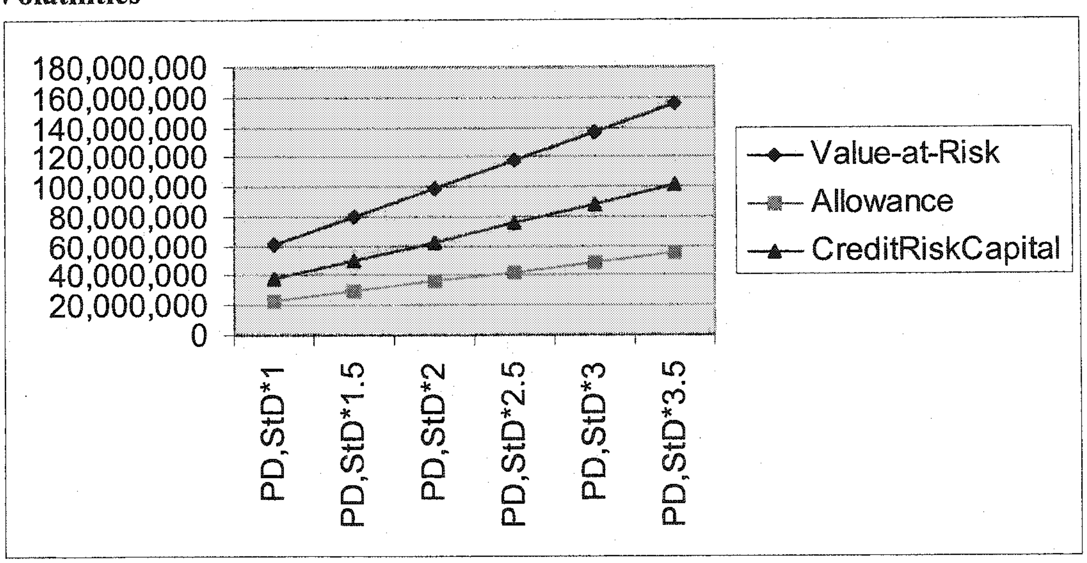
When the standard deviation of default probability increases, the allowance stays the same, but economic capital increases (**Figure 7.5**).

Figure 7.5: Sensitivity of Results to Changes in Volatilities of Default Probabilities



Changes in the volatilities of default probabilities have more effect on overall capital needs than do the changes in default probabilities. When default probabilities double, Value-at-Risk increases by 25%, but when standard deviations of default probabilities double, Value-at-Risk increases by 60%. In both cases, the Value-at-Risk function has an exponential shape: the effect is greater when either the values of the default probabilities or their volatilities are larger.

Figure 7.6: Sensitivity of Results to Changes in Both Default Probabilities and Their Volatilities

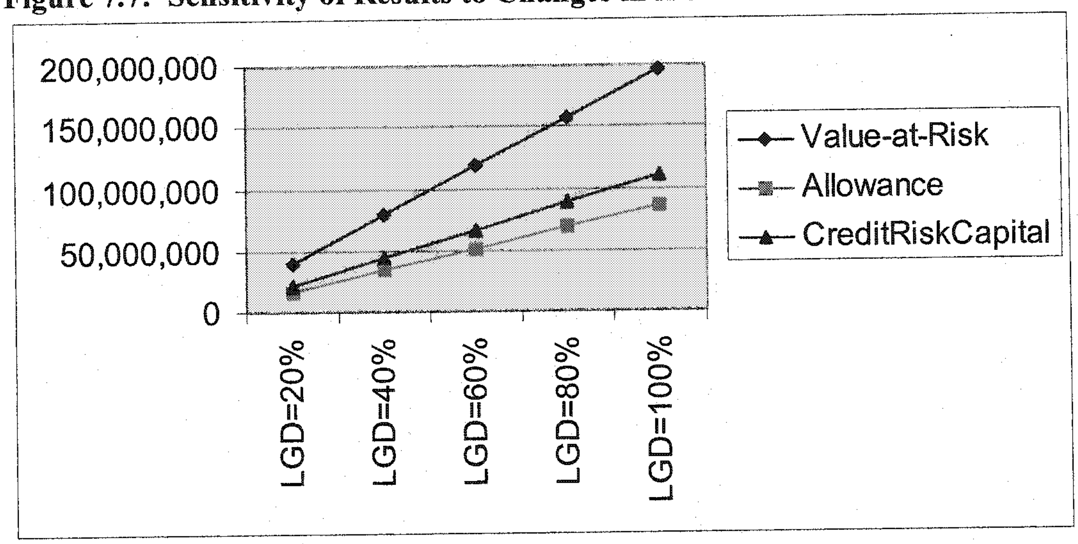


Default probabilities and their volatilities usually increase together, since both are increasing functions of risk ratings. **Figure 7.6** shows the effect of an increase of both default probabilities and their volatilities. Value-at-Risk, economic capital, and allowance increase almost linearly.

The sensitivity test shows that AgStar is still adequately capitalized when default probabilities and their standard deviations triple, which may happen during a recession. AgStar holds $312,231,000 in total risk funds, twice exceeding Value-at-Risk under this stress test.

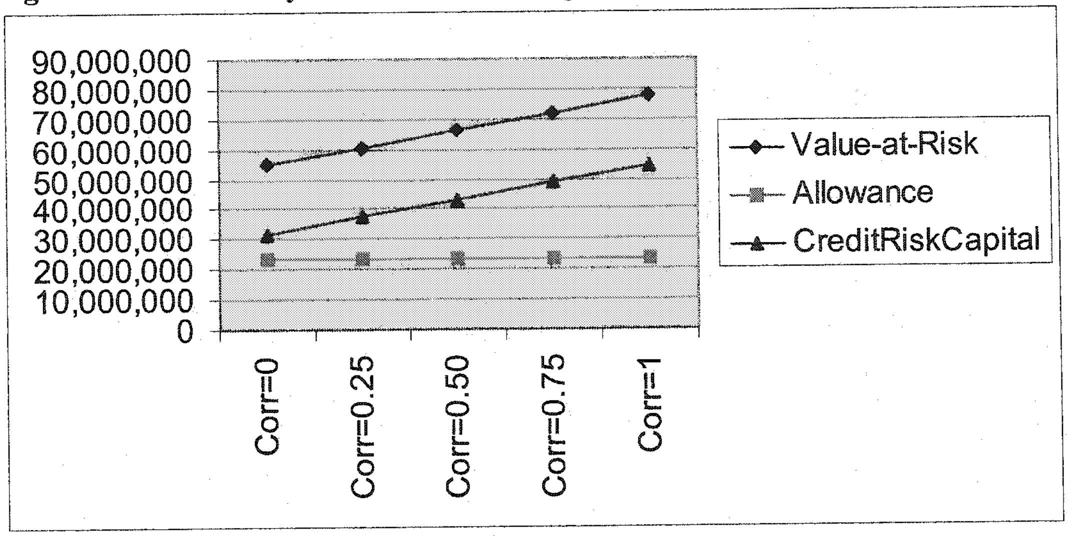
To test model sensitivity to changes in LGD rates, all LGD rates are assigned to various values: 20%, 40%, 60%, 80%, and 100% (see **Figure 7.7**).

Figure 7.7: Sensitivity of Results to Changes in LGD



In the model, required capital is a linear function of LGD. LGD of 100% can be viewed as an extreme shock to the model reflecting the situation when land values decline drastically and/or markets become illiquid. AgStar is still sufficiently capitalized under this shock.

Figure 7.8: Sensitivity of Results to Changes in Correlations



To test the sensitivity of results to changes in default correlations between industries, correlations between all the industries are assigned to the following values: 0; 0.25; 0.50; 0.75; 1 (see **Figure 7.8**). Changes in the correlations do not affect allowance. Economic capital and Value-at-Risk increase by about 50% as correlations increase from zero correlation (independence between all industries) to 1 (perfect correlation between all industries).

It is interesting to note that the actual correlation structure results in a level of Value-at-Risk identical to the one assuming a uniform correlation of 0.25. This is very similar to the assumption of uniform correlation in asset returns of 0.20 used in deriving the regulatory function in the New Basel Capital Accord. This result shows the applicability of Basel's assumption on correlations to agricultural lending.

Minimum exposure is another parameter lenders need to select. **Table 7.21** shows that Value-at-Risk decreases as the minimum exposure becomes larger. As the size of minimum exposure increases, the number of loans exceeding the minimum exposure decreases. Reducing the number of loans slightly decreases diversification, which may raise economic capital. Since there is a large number of loans, reducing the number of loans decreases economic capital because the credit-risk reducing effect of smaller loan volume overpowers the credit-risk increasing effect of decreased diversification.

Table 7.21: Sensitivity of Results to Minimum Exposure

MinExposure	CreditRiskVAR	No. of Loans
1	60,836,685	28,357
10	60,834,934	28,330
100	60,831,049	28,266
1,000	60,811,246	27,934
10,000	60,126,646	22,317
100,000	53,832,005	5,329

Note: The number of loans includes only nondefaulted loans.

Minimum exposure can be set to a larger value when the model needs to execute faster and the results do not need to be very precise. In case of AgStar's data, Value-at-Risk is reduced by only 10%, but the number of loans is reduced in four as the size of minimum exposure increases from 10,000 to 100,000.

The sensitivity stress-testing shows that default probabilities and their volatilities, as well as and loss given default rates are important parameters in the model, while correlation structure and minimum exposure do not have as much effect on overall capital requirements. However, it is important to remember that the accuracy of correlation structure is necessary for the precision in risk contributions which determine capital requirements for individual loans and portfolio segments.

7.7.2 Sensitivity to Model Assumptions

Certain assumptions were made in different stages of developing the model. This section studies the effects of chosen versus other available assumptions on model results. First, the section compares the results under the traditional CreditRisk+ algorithm versus the alternative algorithm employing saddlepoint approximations. Second, the section analyzes the results under default volatilities computed directly per industry versus default volatilities that are usually based on the default volatilities per risk rating.

Traditional Versus Alternative Algorithm

First, model results under the original CreditRisk+ algorithm and the alternative algorithm based on saddlepoint approximation are compared. The algorithms are described in Sections 5.1 and 5.2.1 of the study. Both algorithms can be executed with different speed and precision. Higher precision is achieved through longer computation time. The size of the loss unit controls the precision of the original CreditRisk+ algorithm, since the actual Value-at-Risk gets rounded up to the next largest Value-at-Risk that is a multiple of a loss unit. The number of computed points on the tail of cumulative density function controls the accuracy of the alternative algorithm, since the rest of the points are approximated through linear interpolation.

Table 7.22: Value-at-Risk Under Various Speed/Accuracy of Alternative Algorithms

Loss	No. of Tail Points in Altern. Algorithm			Loss Unit in Original Algorithm		
Percentile	100	1,000	10,000	1,000*	10,000	100,000
90.00%	32,522,867	32,520,935	32,520,907	38,287,765	32,925,387	32,533,393
95.00%	36,362,992	36,361,409	36,361,340	42,718,465	36,812,095	36,383,056
97.00%	39,065,658	39,055,612	39,055,510	45,807,647	39,535,745	39,081,967
98.00%	41,142,301	41,131,013	41,130,999	48,182,995	41,632,943	41,160,827
99.00%	44,594,626	44,575,648	44,575,601	52,121,395	45,113,504	44,610,743
99.50%	47,944,787	47,915,112	47,914,797	55,924,412	48,486,990	47,954,567
99.90%	55,420,110	55,367,081	55,366,798	64,391,972	56,011,795	55,415,251
99.95%	58,528,006	58,476,889	58,476,202	67,924,225	59,150,208	58,527,694
99.97%	60,834,934	60,737,102	60,736,774	70,484,185	61,432,018	60,790,428
99.99%	65,615,834	65,523,226	65,522,101	75,899,485	66,261,481	65,579,646
CPU Time**	20 seconds	2 minutes	15 minutes	22 seconds	4 minutes	3 hours

Notes: *The loss unit is too large to provide accurate results, as Gordy's test (2002) of comparing moments of loss distribution indicates.
**CPU time is given for a Pentium 4, 2.4GHz processor.

Both algorithms are implemented in such a way that smaller Value-at-Risk implies more precise Value-at-Risk. As **Table 7.22** shows, the alternative algorithm is both faster and more precise than the original algorithm.

In using the model, lenders may choose to use different speed/accuracy trade-off. The better the data available, the more precise the model should be. The results throughout the study use the alternative algorithm based on 100 tail points, which seems to be reasonable given the precision of available data, and provide a conservative estimate of the actual Value-at-Risk. Lenders may wish to use high precision when analyzing the effects of adding or removing loans that are small compared to the rest of the portfolio to calculate more accurate risk contributions.

Computing Volatilities of Default Probabilities Directly per Industry

The model requires standard deviations per segment (industry) as an input. CreditRisk+ technical document suggests a convenient way of estimating the standard deviation of a sector as the sum of standard deviations for each client in the sector (CSFP, p. 43), assuming that the credit quality of borrowers within a sector has a more significant influence on the volatility of default than the nature of the sector. Standard deviations are estimated directly per industry in this section to find out the effect of this assumption on results. Columns 2 and 3 of **Table 7.23** show the difference in normalized standard deviations (standard deviations divided by mean default probabilities) between the two methods. The "traditional" method uses the client volatilities of default probabilities (based on default volatilities for each risk rating) to estimate sector default volatilities, while the "direct" method uses the historical time series of default probabilities for each sector directly. There is more variability between the sector standard deviations when they are estimated directly. Directly computed standard deviations are smaller than the traditionally estimated industry standard deviations for the farm economy industries: crops, dairy, swine, other livestock, and landlords. Directly computed standard deviations are greater than the traditionally estimated industry standard deviations for the general economy industries: general farms[41], rural residence, and others.

Table 7.23: Effect of Using Direct Volatilities per Industry

Industry	Industry Sigma*		Risk Contribution**		Economic Capital (%)***	
	Traditional	Direct	Traditional	Direct	Traditional	Direct
Crops	0.64	0.38	265,896	183,545	23.69%	18.26%
Dairy	0.64	0.37	219,554	172,103	11.82%	9.18%
Swine	0.61	0.39	218,961	175,616	17.39%	14.95%
Other Livestock	0.60	0.51	265,313	199,772	5.45%	4.54%
Landlords	0.65	0.32	161,861	166,816	2.78%	2.77%
General Farms	0.62	0.97	198,010	321,058	2.64%	3.47%
Rural Residence	0.66	0.86	149,604	232,393	1.10%	1.29%
Others	0.65	0.83	203,345	298,507	35.13%	45.53%

Note: * Normalized standard deviation per industry.
** Risk Contribution of a new loan with volume $10,000,000, risk rating 3, LGD rating 3, to existing portfolio by industry.
*** Economic capital as a percent of total economic capital per industry.

The resulting levels of Value-at-Risk are almost identical when using directly computed standard deviations: $58,164,316 compared to $60,834,934 for the 99.97th percentile. The allowance for loan loss for the portfolio and individual loans remains the same, but risk contributions are affected by the difference in industry standard deviations (see **Table 7.23**). Economic capital contribution to new loans (Columns 4 and 5) and economic capital requirements per industry (Columns 6 and 7) increase under the direct computation of volatilities for the industries where the volatilities increase, and vice versa.

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[41] The "general farms, primarily crops" industry is assigned by default to small loans originated though the credit desk. Small loans are given primarily to part-time farmers.

The differences in the results may occur for several reasons. First, the traditional approach includes only risk rated borrowers, while standard deviations computed directly by industry are based on all the borrowers per sector, including the ones without a risk rating. Second, there is no need to account for migrations in standard deviations computed directly by industry, since the assigned industry does not usually change as frequently as the risk rating. Third, the assumption that the credit quality of borrowers within a sector has a more significant influence on the volatility of default than the nature of the sector introduces some error in the estimates.

It is hard to tell if the direct computation of industry volatilities is more accurate than the traditional method. Default volatilities by risk rating can be smoothed based on a function of risk rating. In direct computation of volatilities, there is no function for smoothing the values, so they may exhibit more sample variability. Inability to smooth the values can make it hard to estimate default probabilities in sectors with no defaults. In addition, direct computation of default volatilities may be time-consuming to compute as an input for a lender.

Considering the fact that the direct computation of default volatilities produces results similar to the traditional method, the traditional method can be used for convenience. When ample data is available for the accurate estimation of default volatilities directly per sector, it may become a preferred method. It may also result in more precise measures of risk contributions.

7.7.3 Stress-Testing Scenarios

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 for Banking Supervision, 2001):

> 297. A bank must have in place sound stress testing process for use in the assessment of capital adequacy. Stress testing should involve identifying possible events or future changes in economic conditions that could have unfavorable effects on a bank's credit exposures and assessment of the bank's ability to withstand such changes. Three areas that banks could usefully examine are: (i) economic or industry downturns; (ii) market-risk events; and (iii) liquidity conditions.
>
> 298. Stress testing should include specific scenarios that quantitatively assess the impact of broad rating migration of exposures to lower rating grades. Such analysis should also examine the impact of higher default rates and lower recovery rates than a bank's predicted PD, LGD and exposure measurement.

In stress-testing scenarios, shocks can be applied to one or all model parameters: default probabilities, their volatilities, default correlations, and loss given default values. For example, how will a decrease of 50% in recovery rates affect the portfolio? How will a 100% increase in default probabilities in the nonfarm sector affect credit quality of part-time farmers and how will this effect portfolio risk and capital requirements? These changes may be caused by a number of different events, but the question is: how will they affect capital requirements of the whole portfolio and what segments are going to be affected most? The reason for occurrence is not as important as the effect of the occurrence on the portfolio.

Analyzing capital adequacy in probable scenarios would allow for changes in loan allowances. Probable shocks can be applied to each industry to see how they will affect the overall portfolio. An example of a probable scenario could be the doubling of default probabilities and their standard deviations in the swine industry. Sensitivity of each industry to this scenario can be analyzed to identify the loans that should have higher underwriting standards or should be sold to decrease portfolio risk.

Stress-testing scenarios under extreme parameters are used to gauge the lender's potential vulnerability to exceptional but plausible events. An extreme scenario would be similar to the agricultural crisis of the 1980s. The likelihood of a similar crisis occurring in the future is small, but analyzing capital adequacy in such a case would show if a lender is able to withstand a similar crisis. Extreme stress tests can be used to manage the extreme losses (beyond the target insolvency level) by setting concentrations limits.

A scenario modeling the agricultural crisis of 1980s is also an example of a historic stress-test that shows an ability to withstand the worst-case adversities of the past based on the highest rates of default and loss on agricultural loans. In the early and mid-1980s, the farm sector experienced the most severe financial crisis since the Great Depression. About 90% of the losses occurred on loans to commercial farmers. Default losses among corn/soybean farms were the highest of any commercial enterprise, which hit Minnesota the hardest of all states. In Minnesota, 24% of commercial farms faced default in 1984-86, and 10% were technically insolvent (Hanson et. al., Table 10). Land values declined by about 50% during 1981-87.

Table 7.24 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 7.24: 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 volatilities of default probabilities. 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 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 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. The book risk funds show significant shortage under this scenario at the 99.97th percentile. However, the funds are still sufficient under the 95th 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.

CHAPTER 8

SUMMARY AND CONCLUSIONS

8.1 Summary

This study is the first attempt to adapt credit risk models recently introduced in commercial banking to agricultural lending. Credit risk models analyze credit risk, which is the risk from borrower defaults and the primary source of risk in agricultural lending. Credit risk models are recent innovations critical for strategic portfolio management because of their ability to determine capital adequacy and predict and monitor changes in portfolio credit quality. They allow more comprehensive assessments of correlation and concentration in loan portfolios compared to the current practices in Farm Credit System associations. Traditionally, lenders have focused on individual transactions and ignored risk concentrations in their portfolios. This often leads to severe unexpected losses or overcapitalization. Efficient measurement and pricing of credit risks in agricultural loan portfolios increases profitability of a lending institution and enhances its competitive position by estimating credit risk more precisely and increasing the ability to recognize and manage aggregate credit risks. Upcoming regulatory New Basel Capital Accord, planned to be implemented by 2007, is built on the ideas of the credit risk models in order to align regulatory capital requirements closer with actual capital requirements. The input parameters are the same for the New Capital Accord and the credit risk models, making implementation of a credit risk model a preparation for the future regulatory requirements. Agricultural lenders are limited in their ability to apply modern credit risk models, since they cannot use financial market data, and model assumptions may not be appropriate for modeling agricultural risk. Credit risk models have not been adapted to agricultural lending earlier because they are relatively new and quite technical.

The objectives of the study are to identify a credit risk model suitable for agricultural lenders, and to provide guidance to agricultural lenders on using the model to evaluate capital adequacy and to make portfolio management decisions.

The first objective of the study, identification of a credit risk model suitable for agricultural lenders, is achieved through examining the underlying assumptions and data needs of the existing major credit risk models in relationship to modeling credit risk in agriculture. The most appropriate methodology is modified to adapt it to agricultural lending. A framework for modeling credit risk in agriculture and components and methodologies of major credit risk models in commercial lending (KMV's Portfolio Manager, J.P.Morgan's CreditMetrics, McKinsey's CreditPortfolioView, CSFP's CreditRisk+) are analyzed in relationship to credit risk in agricultural lending. A CreditRisk+-type model is deemed most suitable for agricultural lending since its data requirements can be satisfied by the available data, and its assumptions are most appropriate for modeling credit risk in agriculture. The disadvantages of the original CreditRisk+ model are overcome in the study by incorporating recent research (accounting for sector correlations, using more stable and accurate algorithm).

The second objective, providing guidance to agricultural lenders on using the model to evaluate capital adequacy and to make portfolio management decisions, is achieved by applying the model to a representative Farm Credit System association, AgStar Financial Services, ACA. AgStar historical data and the regulatory guidelines of the New Basel Capital Accord are used to determine model parameters: probabilities of default and their volatilities for each risk rating, recovery rates in the event of default, and correlations between industries. The model output is a loan loss distribution, which is used for deriving lender's expected and unexpected losses for the overall portfolio and individual loans. The study explains how this output can be used to evaluate capital adequacy and to conduct portfolio risk analysis. The study shows how the model can be used for the following purposes:

comparing resulting levels of expected losses and economic capital at various insolvency levels to the existing amounts of allowance and book capital, and to regulatory requirements;

monitoring portfolio risk and concentrations;

identifying allowance and economic capital for each segment (by industry/loan type/risk rating/etc.) to analyze concentration risk and set credit limits;

studying the effect of changes in the portfolio composition on allowance and capital requirements (including new loans in various industries, excluding some of the existing loans, portfolio growth);

stress-testing by simulating historical and hypothetical credit events such as changes in risk rating, default levels, and recovery rates; and

using RAROC (Risk-Adjusted Return on Capital) analysis for individual loans, portfolio segments, and the whole portfolio.

8.2 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.

The capital reserve requirements that are derived through the credit risk models provide a benchmark for comparing to the capital reserves that are currently held by Farm Credit System lending institutions. The model shows that AgStar is more than adequately capitalized based on the parameters that are estimated using 1997-2002 data. AgStar's capital position is lower than that of most other FCS associations. This result raises the issue of overcapitalization within the Farm Credit System. Agricultural lenders have increased the amounts of capital in response to the crisis of 1980s instead of actively managing the level of risk in their loan portfolios and relating portfolio risk to the required amount of capital because the modern tools for estimating portfolio risk and capital adequacy are not available. Using the model developed in the study, lenders can quantify the portfolio risk accounting for portfolio effects and determine the amount of capital to support it. By holding an optimal level of capital, lenders may increase their efficiency, and provide for safety and soundness, potential asset growth and long-run institutional viability. Applications of the credit risk model can potentially result in lower aggregate capital requirements. In turn, lower levels of regulatory capital will benefit borrowers in the form of reduced loan rates and greater access to loanable funds.

In general, a portfolio can be effectively managed by focusing on a relatively small number of borrowers that represent a significant portion of portfolio risk. After these borrowers have been identified, AgStar can use several techniques for mitigating credit risk in its portfolio such as selling loans, renewing existing business, managing new business, increasing collateral levels, and using credit derivatives (transferring credit risk to another party, while allowing client relationship to be maintained). While credit derivatives are still relatively new instruments for agricultural lenders, the use of long-term standby agreements and credit swaps is increasing within the Farm Credit System. This model can be used to identify risky exposures as well as to analyze the effect of their potential removal from the portfolio. The effects of adding new loans on portfolio quality and capital requirements can also be analyzed. This may be is useful for risk-based loan pricing.

The model can be used to decrease portfolio credit risk by identifying ways to diversify the loan portfolio. This can be done by setting individual credit limits and risk-based credit limits to borrowers in certain sectors. Portfolio diversification can be measured from the loan loss distribution. A low level of loan diversification is expected to result in a relatively wider spread of the distribution curve (long and fat tail) and a higher level of required capital.

The credit risk model is a potentially powerful instrument for portfolio managers. The information generated by the model is useful to agricultural lenders since it quantifies portfolio risk. This makes it possible to monitor changes in credit risk profile, establish risk-based pricing and develop credit limit systems. However, the outputs of the model are reliable only if the underlying data is comprehensive and meaningful. This means that the lender must have a reliable borrower risk-rating system in place. Borrower risk rating depends on the quality of financial borrower data, which should be updated in a timely manner. Borrower risk ratings should be assigned consistently and reviewed at least annually. Historical data on borrowers, loan performance, and defaults must be archived. This may require the lender to expand the capabilities of its current computer system.

Model parameters must be periodically reviewed to insure that they accurately predict past experience. The results of this application are based on the last five years of data. Yet, that data does not reflect a full economic cycle. Default rates fluctuate over an economic cycle and over time. Thus, parameters necessary for calculating the portfolio loss distribution currently cannot be estimated with a high precision. This problem will be partially solved over time as more years of data become available, but only if historical data is kept beyond the current five-year horizon. Collecting and storing historical data necessary to estimate model parameters is costly for lenders, but more precise parameter estimates may produce lower economic capital requirements. Until sufficient internal data is collected, agricultural lenders can use the regulatory parameters suggested by the New Basel Capital Accord and conservative assumptions.

Model parameters must also reflect expectations about the future. Even if many years of historical data are collected, they may not be representative of the future. Some judgment is necessary to evaluate the degree of relevance of the historical information to future economic conditions.

A recommended solution to the lack of accuracy in the inputs is to use stress-testing. The questionable parameters must be shocked to simulate the results under incorrect parameterization. Stress-testing is also useful for analyzing the results under possible or extreme scenarios that can have unfavorable effects on the lender's portfolio.

The Basel II Capital Accord is currently planned for implementation in 2009 with the transition period starting in 2007. The purpose of this Accord is to introduce a more risk-sensitive capital framework with incentives for good risk management (Morrison). Since the same (or similar) data is required for credit risk models as for the New Basel Capital Accord, the cost of implementing credit risk models is relatively low. Collecting data for implementing the model will prepare associations for the upcoming regulatory requirements of the New Basel Capital Accord.

The credit risk model has important limitations. It cannot be a substitute for management decisions and common sense. The results of the model should not be the only thing used in making portfolio management decisions. These results should be complemented by other information such as the experience and knowledge of loan portfolio managers.

There is a great potential for benefit from the use of the credit risk model in agricultural lending compared to what is common practice among Farm Credit System associations today. The model will increase the transparency and understanding of risks, and assisting managers in their assessment and managing the risks. Hopefully the results of this research will motivate agricultural lenders to collect necessary data and to implement similar models in their institutions.

8.3 Implications for Further Research

The results of this study are based on five years of data that was provided by one agricultural association. It would be interesting to expand the data set used: accumulate data over a longer time series, and collect data from many different agricultural lenders. Since most Farm Credit System associations started accumulating detailed data on borrowers, loans and defaults about three years ago, there will be sufficient data for estimating model parameters in less than a decade. A creation of a pooled and a shared database among associations and other agricultural lenders would greatly facilitate the ability to accurately estimate the input parameters such as default probabilities, loss given default and expected and unexpected losses, since not many single institutions or even groups of institutions have access to the data needed for empirical analysis. In the study, recovery rates are based on regulatory values, which could be verified based on such a data set. Recovery rates could be computed for each loss rating, and volatilities of collateral values could be computed and included in the model. Default probabilities, their volatilities, and correlations between default probabilities in various industries would be more accurate if the effects of macroeconomic variables were incorporated in their estimates, which would be possible with a longer data series. More years of data and a greater number of associations would allow for better model validation by comparing realized and estimated parameters and outcomes.

Another potential area of research is developing models for estimating market and operational risks to complement the credit risk model in estimation of economic capital. These models would require accumulating appropriate data necessary for these models and expanding computer system capabilities in associations.

Additional comparisons between alternative models with respect to agricultural lending could be conducted. This study analyzes the four major credit risk models with respect to agricultural lending, but new models and methods appear constantly.

The effect of using a credit risk model on the efficiency, profitability and portfolio risk of lending institutions could be analyzed. This could be accomplished by comparing two groups of lenders: those who use this tool, and those who do not. Capital adequacy, risk-adjusted return on capital, and portfolio management techniques could be compared between the two groups to study the effect of using the model.

Finally, once the model is in use, the need for its modification to better serve lender's needs could be examined.

REFERENCES

AgriBank, FCB. "Validation of the Term and Operating Scorecards." Memo from C. Mueller and J. Cyr. Credit Letter 99-11. May 5, 1999.

AgriBank, FCB and the Seventh District Associations. 2002 Annual Report. Available at www.AgriBank.com

AgStar Financial Services, ACA. 2002 Annual Report. Available at www.AgStar.com

AgStar Financial Services, ACA. BMIS Training Manual. 2001.

AgStar Financial Services, ACA. Data Dictionary for BMIS. October 13, 2000.

Altman, E.I., and P. Narayanan. "An International Survey of Business Failure Classification Models." *Financial Markets, Instruments and Institutions* Vol. 6, No. 2, 1997.

Anderson, R. "Credit Risk Management." *Presentation at the Annual Meeting of NCT-194.* Kansas, MO, October 6, 2003.

Babetskaya, L.G. "Enhancing the Performance of Risk-Rating Models at Community Banks." Master's Plan B Paper. Department of Applied Economics, University of Minnesota, 2000.

Balzarotti V., C. Castro, and A. Powell. "Reforming Capital Requirements in Emerging Countries: Calibrating Basel II using Historical Argentine Credit Bureau Data and CreditRisk+." Paper presented at World Bank – Financial Stability Institute Workshop in Basel, Switzerland. November 2002.

Balzarotti V., M. Falkenheim, and A. Powell. "On the Use of Portfolio Risk Models and Capital Requirements in Emerging Markets: The Case of Argentina." *The World Bank Economic Review* Vol. 16, No. 2 (2002):197-212.

Barrickman, J., D. Bauer, and J. McKinley. "Predicting Portfolio Credit Quality." *The Journal of Lending & Credit Risk Management* (July 1998):56-62.

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

Barry, P.J., B.J. Sherrick, and P.N. Ellinger. "Farmer Mac's Capital Position." *Journal of Agricultural Lending* Vol. 16, No. 1 (Fall 2002):47-52.

Barry, P.J., B.J. Sherrick, P.N. Ellinger, and D.K. Banner. Risk-based Capital Regulations for Farmer Mac: Loan Loss Estimation Procedures. Barry and Associates, July 1998.

Barry, P.J., B.J. Sherrick, D.A. Lins, B.L. Dixon, and J.R. Brake. "Farm Credit System Insurance Risk Simulation Model." *Agricultural Finance Review* 56(1996):68-84.

Basel Committee on Banking Supervision. "Amendment to the Capital Accord to Incorporate Market Risks." Bank for International Settlements, Basle, Switzerland, January 1996(a). http://www.bis.org/publ/bcbs24.pdf

____________. "Credit Risk Modeling: Current Practices and Applications." Bank for International Settlements, Basle, Switzerland, April 1999. http://www.bis.org/publ/bcbs49.pdf

____________. "Supervisory Framework for the use of "Backtesting" in Conjunction with the Internal Models Approach to Market Risk Capital Requirements." Bank for International Settlements, Basel, Switzerland, January 1996(b). http://www.bis.org/publ/bcbs22.htm

____________. "The New Basel Capital Accord." Bank for International Settlements, Basel, Switzerland, January 2001. http://www.bis.org/publ/bcbsca03.pdf

Berseth, B.D., VP-Portfolio Management at AgStar. Letter to Lyubov Zech and Glenn Pederson. April 17, 2002.

Berry, D.A. and B.W. Lindgren. Statistics: Theory and Methods, second ed. Wadsworth Publishing Company, 1996.

Bjornson, B. and R. Innes. "Another Look at Returns to Agricultural and Nonagricultural Assets." *American Journal of Agricultural Economics* Vol. 74, No. 1 (February 1992):109-119.

Blochwitz, S. and S. Hohl. "Reconciling Ratings." *Risk* Vol. 14, No. 6 (June 2001):87-90.

Bluhm, C., L. Overbeck, and C, Wagner. An Introduction to Credit Risk Modeling. Chapman and Hall/CRC Press LLC, 2003.

Boegelein, L., A. Hamarle, R. Rauhmeier and H. Scheule. "Modeling Default Rate Dynamics in the CreditRisk+ Framework." *Risk* Vol. 15, No. 10 (October 2002):24-28.

Brand, L. and R. Bahar. *Ratings Performance 1997: Stability and Transition.* Standard and Poor's Special Report, January 1998.

Broeker F. and B. Rolfes. "Good Migrations." *Risk* Vol. 11, No. 11 (November 1998):72-73.

Bürgisser, P., A. Kurth, and A. Wagner. "Incorporating Severity Variations into Credit Risk." *The Journal of Risk* Vol. 3, No. 4 (Summer 2001): 5-31.

Bürgisser, P., A. Kurth, A. Wagner, and M. Wolf. "Integrating Correlations." *Risk* Vol. 12, No. 7 (July 1999):57-60.

Caouette, J.B., E.I. Altman, and P. Narayanan. *Managing Credit Risk.* New York: John Wiley & Sons, 1999.

Carey, M. "Dimensions of credit risk and their relationship to economic capital requirements." In: Mishkin, F.S. (ed.), "Prudential supervision: what works and what doesn't." NBER and UC Press, 2001.

Carty, L. and D. Lieberman. *Historical Default Rates of Corporate Bond Issuers 1920-1997.* Moody's Investors Services Special Comment, February 1998.

Cochrane, J.H. *Asset Pricing*. Princeton University Press, 2001.

Committee on the Global Financial System. "A Survey of Stress Tests and Current Practice at Major Financial Institutions." Bank for International Settlements, Basle, Switzerland, April 2001. http://www.bis.org/publ/cgfs18.htm

Credit Suisse Financial Products (CSFP). CreditRisk+: A Credit Risk Management Framework. 1997. http://www.csfb.com/creditrisk/assets/creditrisk.pdf

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

Das S., L. Freed, G. Geng, and N. Kapadia. Correlated Default Risk. Working paper, August 2002.

Ellinger, P.N., N.S. Splett, and P.J. Barry. "Consistency of Credit Evaluations at Agricultural Banks." *Agribusiness: An International Journal* 52(1992):43-56.

ERisk. Economic Capital Bank Survey Methodology. 2002. www.erisk.com.

Falkenstein, E. "Accounting for Economic and Regulatory Capital in RAROC Analysis." *Bank Accounting and Finance* Vol. 11, No. 11 (Fall 1997):29-34.

Farm Financial Standards Council. Financial Guidelines for Agricultural Producers. Naperville, IL, 1995.

Farm Credit Administration. FCA Examination Manual. June 1994. Available at www.fca.gov.

Federal Register. Rules and Regulations. Vol. 66, No. 71. April 12, 2001. Available at www.fca.gov.

Federal Reserve System Task Force on Internal Credit Risk Models. "Credit Risk Models at Major U.S. Banking Institutions: Current State of Art and Implications for Assessment of Capital Adequacy." Board of Governors of the Federal Reserve System, May 1998.

Finger, C. "Sticks and Stones." The RiskMetrics Group, J.P. Morgan and Company, 1999. http://www.riskmetrics.com/pdf/working/sticksstones.pdf

Fischer, M.L. "Financing Agricultural Cooperatives: Economic Issues and Alternatives." Ph.D. Thesis. Department of Applied Economics, University of Minnesota, 1984.

Giese, G. Enhancing CreditRisk+. 2002. http://www.gloriamundi.org/picsresources/gg.pdf

Gordy, M.B. "A Comparative Anatomy of Credit Risk Models." *Journal of Banking and Finance* 24(2000):119-149.

___________. A Risk-Factor Model Foundation for Ratings-Based Bank Capital Rules. Working Paper, Federal Reserve Board, Washington. February 2001.

___________. "Saddlepoint Approximation of CreditRisk+." *Journal of Banking and Finance*, 26(7) (August 2002):1337-1355.

Haaf, H. Some Practical Aspects of Credit Risk Modelling. Commerzbank AG. March 14, 2002.

Hanson, G.D., G.H. Parandvash, and J. Ryan. Loan Repayment Problems of Farmers in the Mid 1980s. Agricultural Economic Report No. 649, Economic Research Service, USDA, September 1991.

Haubenstock, M.J. and C.A. Andrews. "Implementing the New Basel Accord." *The RMA Journal* (December 2001-January 2001):30-35.

Jones, D. and J. Mingo. "Industry Practices in Credit Risk Modeling and Internal Capital Allocations: Implications for a Models-Based Regulatory Capital Standard." Paper presented at the conference "Financial Services at the Crossroads: Capital Regulation in the Twenty-First Century." Federal Reserve Bank of New York, February 26-27.

Kao, D.L. and J.G. Kallberg. "Strategies for Measuring and Managing Risk Concentrations in Loan Portfolios." *The Journal of Commercial Lending* (January 1994):18-27.

KMV Corporation. "Portfolio Manager Overview." http://www.kmv.com

Koyluoglu, H.U., A. Bangia, and T. Garside. "Devil in the Parameters." Oliver, Wyman & Company. Working paper, July 1999.

Koyluoglu, H.U. and A. Hickman. "Reconcilable Differences." *Risk* (October 1998):56-62.

Kurth, A. and D. Tasche. "Credit Risk Contributions to Value-at-Risk and Expected Shortfall." Working paper. November 22, 2002.

Kurth, A., H. Taylor, and A. Wagner. "An Extended Approach to Credit Risk Management." *Economic Notes by Banca Monte dei Paschi di Siena SpA*, Vol.31, No.2 (2002):237-253.

Lehrbass, F. "Rethinking risk-adjusted returns." *Risk*, Credit Risk Special Report (April 1999):35-40.

Lentino, J.V. and H. Pizada. "Issues to Consider in Comparing Credit Risk Management Models." *The Journal of Lending and Credit Risk Management* (December 1998):16-22.

Lieberman, O. "Saddlepoint Approximation for the Distribution of a Ratio of Quadratic Forms in Normal Variables." *Journal of the American Statistical Association* 89 (1994): 924-928.

Lugannani, R. and S. Rice. "Saddlepoint Approximations for the Distribution of the Sum of Independent Random Variables." *Advances in Applied Probability* (December 1980):475-490.

Lula, G. "Loan Portfolio Management – Post FDICIA." *The Journal of Commercial Lending* (November 1993):15-20.

Markowitz, H.M. "Portfolio Selection; Efficient Diversification of Investments." New York, Wiley, 1959.

McAllister, P.M. and J.J. Mingo. "Commercial Loan Risk Management, Credit Scoring, and Pricing: The Need for a New Shared Database." *Journal of Commercial Lending* 76(May 1994):6-20.

McKinley, J.E. and J.R. Barrickman. "Strategic Credit Risk Management." Philadelphia: Robert Morris Associates, 1994.

McKinsey and Co. "Credit Portfolio View." New York: McKinsey and Co., 1997.

Merton, R.C. "On the Pricing of Corporate Debt: The Risk Structure of Interest Rates." *Journal of Finance* 29(1974):449-470.

Mingo, J.J. (compiler) "EDF Estimation: A "Test-Deck" Exercise." *The RMA Journal* (November 2000):54-61.

Morgan, J.P. "CreditMetrics Technical Document." August 1997. http://www.riskmetrics.com/cmtdovv.html

Morrison, J. S. "Preparing for Basel II Modeling Requirements. Part 1: Model Development." *The RMA Journal* (May 2003): 56-61.

Moody's Investor Service, Global Credit Research. "Bank loan Loss Given Default." *Special Comments*, November 2000.

Nickell, P., W. Perraudin and S. Varotto. "Stability of Rating Transitions." *Journal of Banking and Finance* 24(2000):203-227.

Ong, M.K. *Internal Credit Risk Models: Capital Allocation and Performance Measurement.* New York: Risk Publishers, 1999.

Pederson, G. and T. Wilberding. "Strategic Loan Portfolio Management in a Changing Risk Environment." Staff Paper P99-8. Department of Applied Economics, University of Minnesota, September 1999.

Rowe, D. "No Cure Through the Cycle." *Risk* Vol.16, No.3 (March 2003):50.

Rowe, D. "Is 8 % for All Seasons?" *Risk* Vol. 16, No. 5 (May 2003):85.

Schachter, B. "An Irreverent Guide to Value at Risk." *Risks and Rewards* Vol. 33 (March 1998):17-18.

Sharpe, W. F. "Adjusting for Risk in Portfolio Performance Measurement." *Journal of Portfolio Management* (Winter 1975):29-34.

Shepard, L.E. and R.A. Collins. "Why Do Farmers Fail? Farm Bankruptcies 1910-78." *American Journal of Agricultural Economics* 64(November 1982):609-615.

Smithson, C. and G. Hayt. "Optimizing the Allocation of Capital." *The RMA Journal* (July/August 2001):67-72.

Smithson, C. and G. Hayt. "The State of the Art in Credit Portfolio Management." *The RMA Journal* (March 2001):34-38.

Stewart, S. Economic Value Added. Stern Stewart and Co. http://www.sternstewart.com/

Stuart, A. and J.K. Ord. Kendall's Advanced Theory of Statistics, sixth ed., Vol. 1. London: Oxford University Press, 1994.

Treacy, W.F. "Supervisory Standards for Internal Rating System." *The RMA Journal* (November 2000):48-53.

U.S. Congress, House. U.S. Committee of Conference. Providing Credit Assistance to Farmers, to Strengthen the Farm Credit System, to Facilitate the Establishment of Secondary Markets for Agricultural Loans, and for Other Purposes. U.S. House of Representatives Report no. 100-490. Washington, D.C, 18 December 1987.

Vasicek, O. Probability of Loss on Loan Portfolio. KMV Corporation, 1987.

Wilberding, T. "Portfolio Stress-Testing: An Ag Bank Perspective." *The Journal of Lending & Credit Risk Management* Vol. 82, No. 6 (March 2000):80-85.

____________. "Strategic Loan Portfolio Management: An Integrated Approach to Loan Portfolio Management." Approach Document, draft, AgriBank, FCB, St. Paul, MN, June 1999.

____________. "Strategic Credit Risk Management Guide." AgriBank, FCB, St.Paul, MN, June 1997.

Wilde, T. CreditRisk+. In S. Das (Editor), Credit Derivatives and Credit Linked Notes (2nd Edition) pp.589-628. Wiley, 2000.

Wilde, T. "The IRB Approach Explained." *Risk* Vol. 14, No. 5 (May 2001): 87-90.

Wilson, T. "Portfolio Credit Risk (I)" *Risk Magazine* (September 1997):111-117, and "Portfolio Credit Risk (II)" *Risk Magazine* (October 1997):56-61.

APPENDICES

Appendix A. Tables

Table A.1: Calculation of Default Probabilities for 1998-2002 by Risk Rating

Rating	2001 Clients	2002 Defaults	2002 PD	2000 Clients	2001 Defaults	2001 PD	1999 Clients	2000 Defaults	2000 PD
1	1108	1	0.09%	1155	1	0.09%	1225	1	0.08%
2	1727	8	0.46%	1771	2	0.11%	1943	3	0.15%
3	1767	7	0.40%	1616	4	0.25%	1849	12	0.65%
4	1613	24	1.49%	1541	23	1.49%	1609	17	1.06%
5	370	14	3.78%	355	15	4.23%	378	11	2.91%
6	115	9	7.83%	132	14	10.61%	165	18	10.91%
7	140	19	13.57%	173	17	9.83%	183	26	14.21%
8	0	0	100.00%	0	0	100.00%	0	0	100.00%
9	0	0	100.00%	0	0	100.00%	0	0	100.00%
Rated	6840	82	1.20%	6743	76	1.13%	7352	88	1.20%
Total	14461	246	1.70%	13015	114	0.88%	13348	115	0.86%
Nonrated	7621	164	2.15%	6272	38	0.61%	5996	27	0.45%

Rating	1998 Clients	1999 Defaults	1999 PD	1997 Clients	1998 Defaults	1998 PD
1	1218	3	0.25%	1193	1	0.08%
2	2062	16	0.78%	2122	23	1.08%
3	1612	18	1.12%	1259	31	2.46%
4	1335	33	2.47%	789	29	3.68%
5	229	10	4.37%	166	16	9.64%
6	172	18	10.47%	111	22	19.82%
7	114	22	19.30%	26	10	38.46%
8	1	1	100.00%	0	0	100.00%
9	0	0	100.00%	0	0	100.00%
Rated	6743	121	1.79%	5666	132	2.33%
Total	15129	179	1.18%	15417	231	1.50%
Nonrated	8386	58	0.69%	9751	99	1.02%

Table A.2: Calculation of Default Probabilities for 1998-2002 by Industry

Industry	2001 Clients	2002 Defaults	2002 PD	2000 Clients	2001 Defaults	2001 PD	1999 Clients	2000 Defaults	2000 PD
Crops	4695	35	0.75%	5193	28	0.54%	5309	37	0.70%
Gen.Farms	1780	96	5.39%	611	4	0.66%	642	4	0.62%
Dairy	2213	20	0.90%	2524	22	0.87%	2763	30	1.09%
Swine	951	8	0.84%	932	14	1.50%	973	9	0.93%
OtherLivest.	939	9	0.96%	868	7	0.81%	947	12	1.27%
Landlord	1792	14	0.78%	1808	8	0.44%	1900	8	0.42%
Rur.Res.	1192	32	2.69%	792	22	2.78%	605	5	0.83%
Others	899	32	3.56%	894	9	1.01%	846	10	1.18%
Total	14461	246	1.70%	13622	114	0.84%	13985	115	0.82%

Industry	1998 Clients	1999 Defaults	1999 PD	1997 Clients	1998 Defaults	1998 PD
Crops	5459	66	1.21%	5183	68	1.31%
Gen.Farms	683	9	1.32%	869	19	2.19%
Dairy	3197	30	0.94%	3224	60	1.86%
Swine	1119	24	2.15%	1073	19	1.77%
OtherLivest.	990	20	2.02%	1235	33	2.67%
Landlord	1946	16	0.82%	1915	10	0.52%
Rur.Res.	443	2	0.45%	313	1	0.32%
Others	1969	12	0.61%	2468	21	0.85%
Total	15806	179	1.13%	16280	231	1.42%

Appendix B. Microsoft Access Queries

Query B.1: Selecting Non-defaulted Customers in 2001 in Risk Rating 1

```
SELECT CUST_GENERAL_Y01.CIF_NBR
FROM LOAN_BILLING_Y01 INNER JOIN ((LOAN_DETAIL2_Y01 INNER JOIN
LOAN_HISTORY_Y01 ON LOAN_DETAIL2_Y01.LOAN_NBR =
LOAN_HISTORY_Y01.LOAN_NBR) INNER JOIN (CUST_GENERAL_Y01 INNER JOIN
LOAN_DETAIL1_Y01 ON CUST_GENERAL_Y01.CIF_NBR =
LOAN_DETAIL1_Y01.CIF_NBR) ON LOAN_HISTORY_Y01.LOAN_NBR =
LOAN_DETAIL1_Y01.LOAN_NBR) ON LOAN_BILLING_Y01.LOAN_NBR =
LOAN_DETAIL2_Y01.LOAN_NBR
WHERE (((CUST_GENERAL_Y01.RISK_RATING) Like "*1") AND
((LOAN_DETAIL1_Y01.DATE_STOP_ACCRUAL) Not Like "*") AND
((LOAN_DETAIL1_Y01.LOAN_STATUS)<>"P") AND
((LOAN_HISTORY_Y01.CHARGE_OFF_YTD) Like "0" Or
(LOAN_HISTORY_Y01.CHARGE_OFF_YTD) Like "") AND
((LOAN_DETAIL2_Y01.RESTRUCT_IND)<>"1" And
(LOAN_DETAIL2_Y01.RESTRUCT_IND)<>"2") AND
((LOAN_DETAIL2_Y01.BNKRPTCY_FRCLS_CD)="") AND
((LOAN_BILLING_Y01.PAST_DUE_DAYS)<90))
GROUP BY CUST_GENERAL_Y01.CIF_NBR;
```

Query B.2: Selecting Defaulted Customers in 2002 in Risk Rating 1

```
SELECT CUST_GENERAL_Y01.CIF_NBR
FROM (((LOAN_BILLING_Y01 INNER JOIN LOAN_BILLING_Y02 ON
LOAN_BILLING_Y01.LOAN_NBR = LOAN_BILLING_Y02.LOAN_NBR) INNER JOIN
((LOAN_DETAIL2_Y01 INNER JOIN LOAN_DETAIL2_Y02 ON
LOAN_DETAIL2_Y01.LOAN_NBR = LOAN_DETAIL2_Y02.LOAN_NBR) INNER JOIN
(LOAN_DETAIL1_Y01 INNER JOIN (CUST_GENERAL_Y01 INNER JOIN
LOAN_DETAIL1_Y02 ON CUST_GENERAL_Y01.CIF_NBR =
LOAN_DETAIL1_Y02.CIF_NBR) ON LOAN_DETAIL1_Y01.CIF_NBR =
LOAN_DETAIL1_Y02.CIF_NBR) ON LOAN_DETAIL2_Y02.LOAN_NBR =
LOAN_DETAIL1_Y02.LOAN_NBR) ON LOAN_BILLING_Y02.LOAN_NBR =
LOAN_DETAIL2_Y02.LOAN_NBR) INNER JOIN LOAN_HISTORY_Y02 ON
LOAN_DETAIL1_Y02.LOAN_NBR = LOAN_HISTORY_Y02.LOAN_NBR) INNER JOIN
LOAN_HISTORY_Y01 ON LOAN_HISTORY_Y02.LOAN_NBR =
LOAN_HISTORY_Y01.LOAN_NBR
WHERE (((CUST_GENERAL_Y01.RISK_RATING) Like "*1") AND
((LOAN_DETAIL1_Y01.DATE_STOP_ACCRUAL) Not Like "*") AND
((LOAN_DETAIL1_Y02.DATE_STOP_ACCRUAL)>#12/31/2001#) AND
((LOAN_DETAIL2_Y01.BNKRPTCY_FRCLS_CD)="") AND
((LOAN_DETAIL2_Y01.RESTRUCT_IND)<>"1" And
(LOAN_DETAIL2_Y01.RESTRUCT_IND)<>"2") AND
((LOAN_BILLING_Y01.PAST_DUE_DAYS)<=90) AND
((LOAN_HISTORY_Y01.CHARGE_OFF_YTD)=0 Or
(LOAN_HISTORY_Y01.CHARGE_OFF_YTD) Like "")) OR
(((CUST_GENERAL_Y01.RISK_RATING) Like "*1") AND
((LOAN_DETAIL1_Y01.DATE_STOP_ACCRUAL) Not Like "*") AND
((LOAN_DETAIL2_Y02.DATE_LITG_EFFECT)>#12/31/2001#) AND
((LOAN_DETAIL2_Y01.BNKRPTCY_FRCLS_CD)="") AND
((LOAN_DETAIL2_Y01.RESTRUCT_IND)<>"1" And
(LOAN_DETAIL2_Y01.RESTRUCT_IND)<>"2") AND
((LOAN_BILLING_Y01.PAST_DUE_DAYS)<=90) AND
((LOAN_HISTORY_Y01.CHARGE_OFF_YTD)=0 Or
(LOAN_HISTORY_Y01.CHARGE_OFF_YTD) Like "")) OR
(((CUST_GENERAL_Y01.RISK_RATING) Like "*1") AND
((LOAN_DETAIL1_Y01.DATE_STOP_ACCRUAL) Not Like "*") AND
((LOAN_DETAIL2_Y01.BNKRPTCY_FRCLS_CD)="") AND
((LOAN_DETAIL2_Y02.RESTRUCT_IND)="1" Or
(LOAN_DETAIL2_Y02.RESTRUCT_IND)="2") AND
((LOAN_DETAIL2_Y01.RESTRUCT_IND)<>"1" And
(LOAN_DETAIL2_Y01.RESTRUCT_IND)<>"2") AND
((LOAN_BILLING_Y01.PAST_DUE_DAYS)<=90) AND
```

```
((LOAN_HISTORY_Y01.CHARGE_OFF_YTD)=0 Or
(LOAN_HISTORY_Y01.CHARGE_OFF_YTD) Like "")) OR
(((CUST_GENERAL_Y01.RISK_RATING) Like "*1") AND
((LOAN_DETAIL1_Y01.DATE_STOP_ACCRUAL) Not Like "*") AND
((LOAN_DETAIL2_Y01.BNKRPTCY_FRCLS_CD)="") AND
((LOAN_DETAIL2_Y01.RESTRUCT_IND)<>"1" And
(LOAN_DETAIL2_Y01.RESTRUCT_IND)<>"2") AND
((([LOAN_BILLING_Y02].[PAST_DUE_90_DAYS])-
([LOAN_BILLING_Y01].[PAST_DUE_90_DAYS]))>0) AND
((LOAN_BILLING_Y01.PAST_DUE_DAYS)<=90) AND
((LOAN_HISTORY_Y01.CHARGE_OFF_YTD)=0 Or
(LOAN_HISTORY_Y01.CHARGE_OFF_YTD) Like "")) OR
(((CUST_GENERAL_Y01.RISK_RATING) Like "*1") AND
((LOAN_DETAIL1_Y01.DATE_STOP_ACCRUAL) Not Like "*") AND
((LOAN_DETAIL2_Y01.BNKRPTCY_FRCLS_CD)="") AND
((LOAN_DETAIL2_Y01.RESTRUCT_IND)<>"1" And
(LOAN_DETAIL2_Y01.RESTRUCT_IND)<>"2") AND
((([LOAN_BILLING_Y02].[PAST_DUE_120_DAYS])-
([LOAN_BILLING_Y01].[PAST_DUE_120_DAYS]))>0) AND
((LOAN_BILLING_Y01.PAST_DUE_DAYS)<=90) AND
((LOAN_HISTORY_Y01.CHARGE_OFF_YTD)=0 Or
(LOAN_HISTORY_Y01.CHARGE_OFF_YTD) Like "")) OR
(((CUST_GENERAL_Y01.RISK_RATING) Like "*1") AND
((LOAN_DETAIL1_Y01.DATE_STOP_ACCRUAL) Not Like "*") AND
((LOAN_DETAIL2_Y01.BNKRPTCY_FRCLS_CD)="") AND
((LOAN_DETAIL2_Y01.RESTRUCT_IND)<>"1" And
(LOAN_DETAIL2_Y01.RESTRUCT_IND)<>"2") AND
((LOAN_HISTORY_Y02.CHARGE_OFF_YTD)>0) AND
((LOAN_BILLING_Y01.PAST_DUE_DAYS)<=90) AND
((LOAN_HISTORY_Y01.CHARGE_OFF_YTD)=0 Or
(LOAN_HISTORY_Y01.CHARGE_OFF_YTD) Like ""))
GROUP BY CUST_GENERAL_Y01.CIF_NBR;
```

Query B.3: Selecting Ending Risk Ratings for Clients with Beginning Risk Rating 1 in 2001-2002 Risk Migrations

First, the following query selects clients that are not in default in the beginning and ending periods as `QueryNonDef0102migr`:

```
SELECT CUST_GENERAL_Y01.CIF_NBR
FROM (((LOAN_BILLING_Y02 INNER JOIN LOAN_DETAIL1_Y02 ON
LOAN_BILLING_Y02.LOAN_NBR = LOAN_DETAIL1_Y02.LOAN_NBR) INNER JOIN
LOAN_HISTORY_Y02 ON LOAN_DETAIL1_Y02.LOAN_NBR =
LOAN_HISTORY_Y02.LOAN_NBR) INNER JOIN LOAN_DETAIL2_Y02 ON
LOAN_HISTORY_Y02.LOAN_NBR = LOAN_DETAIL2_Y02.LOAN_NBR) INNER JOIN
(CUST_GENERAL_Y02 INNER JOIN (LOAN_BILLING_Y01 INNER JOIN
((LOAN_DETAIL2_Y01 INNER JOIN LOAN_HISTORY_Y01 ON
LOAN_DETAIL2_Y01.LOAN_NBR = LOAN_HISTORY_Y01.LOAN_NBR) INNER JOIN
(CUST_GENERAL_Y01 INNER JOIN LOAN_DETAIL1_Y01 ON
CUST_GENERAL_Y01.CIF_NBR = LOAN_DETAIL1_Y01.CIF_NBR) ON
LOAN_HISTORY_Y01.LOAN_NBR = LOAN_DETAIL1_Y01.LOAN_NBR) ON
LOAN_BILLING_Y01.LOAN_NBR = LOAN_DETAIL2_Y01.LOAN_NBR) ON
CUST_GENERAL_Y02.CIF_NBR = CUST_GENERAL_Y01.CIF_NBR) ON
LOAN_DETAIL2_Y02.CIF_NBR = CUST_GENERAL_Y02.CIF_NBR
WHERE (((LOAN_DETAIL1_Y01.DATE_STOP_ACCRUAL) Not Like "*") AND
((LOAN_DETAIL1_Y02.DATE_STOP_ACCRUAL) Not Like "*") AND
((LOAN_DETAIL1_Y01.LOAN_STATUS)<>"P") AND
((LOAN_HISTORY_Y01.CHARGE_OFF_YTD) Like "0" Or
(LOAN_HISTORY_Y01.CHARGE_OFF_YTD) Like "") AND
((LOAN_HISTORY_Y02.CHARGE_OFF_YTD) Like "0" Or
(LOAN_HISTORY_Y02.CHARGE_OFF_YTD) Like "") AND
((LOAN_DETAIL2_Y01.RESTRUCT_IND)<>"1" And
```

```
(LOAN_DETAIL2_Y01.RESTRUCT_IND)<>"2") AND
((LOAN_DETAIL2_Y02.RESTRUCT_IND)<>"1" And
(LOAN_DETAIL2_Y02.RESTRUCT_IND)<>"2") AND
((LOAN_DETAIL2_Y01.BNKRPTCY_FRCLS_CD)="") AND
((LOAN_DETAIL2_Y02.BNKRPTCY_FRCLS_CD)="") AND
((LOAN_BILLING_Y01.PAST_DUE_DAYS)<90) AND
((LOAN_BILLING_Y02.PAST_DUE_DAYS)<90))
GROUP BY CUST_GENERAL_Y01.CIF_NBR;
```

Next, ending risk ratings in 2002 are selected using the result of previous query as `QueryNonDef0102migr`:

```
SELECT CUST_GENERAL_Y02.RISK_RATING, Count(CUST_GENERAL_Y02.CIF_NBR) AS
CountOfCIF_NBR
FROM (CUST_GENERAL_Y02 INNER JOIN CUST_GENERAL_Y01 ON
CUST_GENERAL_Y02.CIF_NBR = CUST_GENERAL_Y01.CIF_NBR) INNER JOIN
QueryNonDef0102migr ON CUST_GENERAL_Y01.CIF_NBR =
QueryNonDef0102migr.CIF_NBR
WHERE (((CUST_GENERAL_Y01.RISK_RATING) Like "*1"))
GROUP BY CUST_GENERAL_Y02.RISK_RATING;
```

Query B.4: Selecting Loans Participating in Master-Sold Agreements Combined by Customer

First, the following query result is saved as `LoanExposuresGross`:

```
SELECT CUST_GENERAL_Y02.CIF_NBR, LOAN_DETAIL1_Y02.ENTITY_CODE,
CUST_GENERAL_Y02.BRANCH_NBR, CUST_GENERAL_Y02.COUNTY_CODE,
CUST_GENERAL_Y02.CUST_AG_BUSINESS,
CUST_GENERAL_Y02.CUST_AG_BUSINESS_DESC,
CUST_GENERAL_Y02.CUST_INVOLVEMENT, CUST_GENERAL_Y02.RISK_RATING,
LOAN_DETAIL1_Y02.LOAN_NBR, LOAN_DETAIL1_Y02.ACCRUAL_CODE,
LOAN_DETAIL1_Y02.LOAN_TYPE, LOAN_DETAIL1_Y02.VOLUME,
LOAN_DETAIL1_Y02.UNFUNDED_BALANCE, LOAN_DETAIL2_Y02.LOAN_GUAR_IND,
LOAN_DETAIL2_Y02.LOAN_GUAR_PCT, LOAN_DETAIL2_Y02.CREDIT_SCORE,
LOAN_DETAIL2_Y02.RISK_RATING, LOAN_DETAIL2_Y02.USER_CODE_6,
LOAN_MCD_Y02.COST_CENTER_NBR, LOAN_COLLATERAL_Y02.COLLATERAL_CODE,
LOAN_COLLATERAL_Y02.COLL_SHORT_DESC,
LOAN_DETAIL3_Y02.PARTIC_BASIS_CODE, LOAN_DETAIL2_Y02.RESTRUCT_IND,
LOAN_BILLING_Y02.PAST_DUE_DAYS, LOAN_HISTORY_Y02.CHARGE_OFF_YTD,
LOAN_DETAIL2_Y02.BNKRPTCY_FRCLS_CD, LOAN_COLLATERAL_Y02.NRV_TOTAL
FROM LOAN_HISTORY_Y02 INNER JOIN (LOAN_BILLING_Y02 INNER JOIN
((LOAN_COLLATERAL_Y02 INNER JOIN LOAN_DETAIL3_Y02 ON
LOAN_COLLATERAL_Y02.LOAN_NBR = LOAN_DETAIL3_Y02.LOAN_NBR) INNER JOIN
(((CUST_GENERAL_Y02 INNER JOIN LOAN_DETAIL1_Y02 ON
CUST_GENERAL_Y02.CIF_NBR = LOAN_DETAIL1_Y02.CIF_NBR) INNER JOIN
LOAN_DETAIL2_Y02 ON LOAN_DETAIL1_Y02.LOAN_NBR =
LOAN_DETAIL2_Y02.LOAN_NBR) INNER JOIN LOAN_MCD_Y02 ON
LOAN_DETAIL2_Y02.LOAN_NBR = LOAN_MCD_Y02.LOAN_NBR) ON
LOAN_COLLATERAL_Y02.LOAN_NBR = LOAN_MCD_Y02.LOAN_NBR) ON
LOAN_BILLING_Y02.LOAN_NBR = LOAN_COLLATERAL_Y02.LOAN_NBR) ON
LOAN_HISTORY_Y02.LOAN_NBR = LOAN_BILLING_Y02.LOAN_NBR
WHERE (((LOAN_DETAIL1_Y02.LOAN_STATUS)<>"P"));
```

Next, the following query is executed using the result of previous query as table LoanExposuresGross:

```
SELECT DISTINCT LoanExposuresGross.CIF_NBR,
LoanExposuresGross.ENTITY_CODE, LoanExposuresGross.BRANCH_NBR,
LoanExposuresGross.COUNTY_CODE, LoanExposuresGross.CUST_AG_BUSINESS,
LoanExposuresGross.CUST_AG_BUSINESS_DESC,
```

```
LoanExposuresGross.CUST_INVOLVEMENT,
LoanExposuresGross.CUST_GENERAL_Y02.RISK_RATING,
Max(LoanExposuresGross.ACCRUAL_CODE) AS MaxOfACCRUAL_CODE,
LoanExposuresGross.LOAN_TYPE, Sum(LoanExposuresGross.VOLUME) AS
SumOfVOLUME, Sum(LoanExposuresGross.UNFUNDED_BALANCE) AS
SumOfUNFUNDED_BALANCE, First(LoanExposuresGross.LOAN_GUAR_IND) AS
FirstOfLOAN_GUAR_IND, First(LoanExposuresGross.LOAN_GUAR_PCT) AS
FirstOfLOAN_GUAR_PCT, Min(LoanExposuresGross.CREDIT_SCORE) AS
MinOfCREDIT_SCORE, Min(LoanExposuresGross.CUST_GENERAL_Y02.RISK_RATING)
AS Expr1, First(LoanExposuresGross.USER_CODE_6) AS FirstOfUSER_CODE_6,
LoanExposuresGross.COST_CENTER_NBR,
First(LoanExposuresGross.COLLATERAL_CODE) AS FirstOfCOLLATERAL_CODE,
First(LoanExposuresGross.COLL_SHORT_DESC) AS FirstOfCOLL_SHORT_DESC,
Max(LoanExposuresGross.RESTRUCT_IND) AS MaxOfRESTRUCT_IND,
Max(LoanExposuresGross.PAST_DUE_DAYS) AS MaxOfPAST_DUE_DAYS,
Max(LoanExposuresGross.CHARGE_OFF_YTD) AS MaxOfCHARGE_OFF_YTD,
Max(LoanExposuresGross.BNKRPTCY_FRCLS_CD) AS MaxOfBNKRPTCY_FRCLS_CD
FROM LoanExposuresGross
WHERE (((LoanExposuresGross.PARTIC_BASIS_CODE)="M" Or
(LoanExposuresGross.PARTIC_BASIS_CODE)="S"))
GROUP BY LoanExposuresGross.CIF_NBR, LoanExposuresGross.ENTITY_CODE,
LoanExposuresGross.BRANCH_NBR, LoanExposuresGross.COUNTY_CODE,
LoanExposuresGross.CUST_AG_BUSINESS,
LoanExposuresGross.CUST_AG_BUSINESS_DESC,
LoanExposuresGross.CUST_INVOLVEMENT,
LoanExposuresGross.CUST_GENERAL_Y02.RISK_RATING,
LoanExposuresGross.LOAN_TYPE, LoanExposuresGross.COST_CENTER_NBR
ORDER BY LoanExposuresGross.CIF_NBR;
```