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Credit Risk Models: An Application to Agricultural Lending

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Agricultural Finance Markets in Transition

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Ani L. Katchova and Peter J. Barry*

Abstract

Credit risk models are developed and used to estimate capital requirements for agricultural lenders under the New Basel Capital Accord. The theoretical models combine Merton's distance-to-default approach with credit value-at-risk methodologies. Two applied models, CreditMetrics and KMV, are illustrated using farm financial data. Expected and unexpected losses for a portfolio of farms are calculated using probability of default, loss given default, and portfolio risk measures. The results show that credit quality and correlations among farms play a significant role in risk pricing for agricultural lenders.

Key words: credit risk, credit scoring, credit value-at-risk, debt, default, New Basel Accord.

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Credit Risk Models: An Application to Agricultural Lending

Recent advancements in the measurement and management of credit risk are emphasizing the use of frequency and severity of loan default concepts, in a Value-at-Risk (VaR) framework, to determine the economic capital needed by financial institutions to backstop these risks. The New Basel Accord to be implemented in 2006 is following this approach. The Accord will bring global capital regulation guidelines for financial institutions in line with industry best practice and offer institutions a range of approaches to meet regulatory capital requirements, commensurate with the institutions' size, scope of operations, and available resources.

The goals of these advancements are to sharpen the precision and granularity (i.e. grouping of homogenous borrowers) of risk ratings, to relate these ratings more closely to capital needs and, where possible, to conserve costly holdings of institutional capital. In U.S. agriculture, for example, farmers provided nearly \$20 billion of equity capital, loan loss reserves and insurance program assets in 2002 to ensure safety and soundness of the cooperative Farm Credit System, as well as pay about \$36.7 million annually for the regulatory costs of the Farm Credit Administration (Barry). Reductions in excessive capital holdings (if the results show excessive capital) would free funds for other productive uses. Alternatively, increases in capital holdings (if results show insufficient capital) would increase the solvency of agricultural lenders.

It is widely recognized that data needed for measuring VaR credit risks are a limiting factor. Under the New Basel Accord, probabilities of default and loss given default can be measured using internal institutional data or obtained as external data. Using internal data requires a wide cross-section and lengthy time-series of loss and non-loss experiences to generate reliable default measures. The New Accord initially requires at least five years of data history, while clearly recognizing that longer series are preferred. In the absence of internal data, the use of external data requires that the quality of the institution's loan portfolio and borrower characteristics are matched to those of an external source.¹

Agricultural lending has several unique characteristics, which influence capital requirements. The agricultural sector is characterized by a lengthy production cycle which often leads to less frequent, seasonal payments of loans (Barry). The sector is capital intensive with more than 90% of total assets consisting of farm real estate and machinery. Financial performance of farms can be highly correlated, especially for farms with similar typology and close geographical location. Because financial institutions, especially agricultural lenders, usually do not hold random portfolios of loans, geographic and industry correlations lead to higher correlations in default and losses (Bliss).

The goals of this paper are to develop credit risk models that meet capital requirements for agricultural lenders under the New Basel Capital Accord and to estimate these models using farm-level data. The theoretical models will combine Merton's option pricing approach and credit value-at-risk methodologies. These models will be estimated for the portfolio of all farms and also by grouping farms into different credit quality classes using two applied models, CreditMetrics and the KMV.

¹ Alternative approaches include the use of the borrower's data to determine "distance to default," mark-to-market methods, mapping from external credit rating agencies, and borrower simulation models (Altman and Saunders; Crouhy, Galai, and Mark; Carey and Hrycay).

Theoretical Models

The theoretical models are based on Merton's option pricing approach and credit value-at-risk methodologies. In applying Merton's model to agriculture, credit risk is driven by the dynamics of farm assets of the farmer-borrower. A probability of default and loss given default are calculated using the values of assets and debts. Capital requirements for financial institutions are calculated using credit VaR methodologies, which estimate probability distributions of credit losses conditional on portfolio composition (Sherrick, Barry, and Ellinger; and Barry et al.).

Merton's Model

Following Merton, many finance studies have assumed that the value of firm's assets follows a geometric Brownian motion. Similarly, Stokes and Brinch assume that land values (the most significant asset in agriculture) follow a geometric Brownian motion. Consistent with these studies, the value of farm assets is assumed to follow a standard geometric Brownian motion,

$$(1) \quad A_{it} = A_{i0} \exp \left\{ (\mu_i - \sigma_i^2 / 2)t + \sigma_i \sqrt{t} z_t \right\},$$

where A_{it} is farm i 's assets at time t , μ_i and σ_i^2 are the mean and variance of the instantaneous rate of return on farm i 's assets (dA_{it} / A_{it}), and $z_t \sim N(0,1)$. The value of farm assets A_{it} is lognormally distributed which implies that the log-asset returns r_{it} follow a normal distribution.

Default occurs when a farmer misses a debt payment most likely due to a shortfall in cash flows. However, if the farm is solvent, i.e. the value of assets is greater than the value of debt, debt can be re-financed and liquidation avoided. Following other finance studies, default is assumed to occur at the end of the period when the value of farm assets A_{it} is less than the value of farm debt D_{it} (Crouhy, Galai, and Mark).² The probability of default PD_{it} , thus, is

$$(2) \quad PD_{it} = \Pr [A_{it} \leq D_{it}].$$

After substituting equation (1) into equation (2) and simplifying, it follows that

$$(3) \quad PD_{it} = \Pr \left[z_t \leq -\frac{\ln[A_{it} / D_{it}] + (\mu_i - \sigma_i^2 / 2)t}{\sigma_i \sqrt{t}} \right] \equiv N(-DD_{it}),$$

where

$$(4) \quad DD_{it} \equiv \frac{\ln[A_{it} / D_{it}] + (\mu_i - \sigma_i^2 / 2)t}{\sigma_i \sqrt{t}}$$

is called distance to default and $N(\cdot)$ is the standard normal cumulative density function (Crouhy, Galai, and Mark).

Figure 1 shows how the values of stochastic assets and deterministic debt evolve over time, with default occurring when the value of assets falls below the value of debt. The figure

² This default condition is equivalent to technical bankruptcy in which the borrower has no equity remaining after all financial obligations are met.

illustrates the distribution of the value of farm assets relative to debt obligations, the distance to default, and the probability of default. The distance to default depends on the margin of equity between asset and debt values as well as the expected growth and variance of asset returns. The shaded area is the probability of default (i.e. the probability that the value of assets will be less than the value of debt) which is a function of the distance to default.

The probability of default for each farm is calculated using the properties of the normal distribution as the probability that assets will fall below debt. The average probability of default, PD , is calculated as the weighted average of the probability of default for all farms, weighted by the debt for each farm. Instead of using this calculated statistical probability of default, several studies use the actual historical default rate calculated from historical data (Crouhy, Galai, and Mark). The historical default rate can be calculated as either the percent debt in default or as the percent farms in default. Lenders often report the percent debt in default because this measure reflects more directly the impact on capital and loan profitability. The two measures will not necessarily be similar if the average debt levels of defaulting farms differ substantially from those of non-defaulting farms. This study calculates both the statistical probability of default and the historical default rate.

Credit Risk and Capital Requirements Calculation

When measuring credit risk, two methods are commonly used to determine portfolio value (Garside, Stott, and Stevens). Under the NPV-based (net present value) method, the forward value of debt is determined using mark-to-market models as the sum of future debt payments discounted at the appropriate risk-adjusted discount rates for the respective rating classes (Crouhy, Galai, and Mark). Under the loss-based method, losses due to credit risk are calculated directly using historical data on defaults and loss given default. The NPV-based method is applicable to bond portfolios and large corporate portfolios where market trade data are available. However, most institutions use the loss-based method. Because the debt and equity claims of farm businesses are not traded in active secondary markets, the loss-based method is used here to calculate losses due to credit risk.

In case of default, the loan value is lost in full, part, or none depending on the quality of collateral pledged to secure the loan, the seniority of claims, possible loan guarantees, and administrative costs. In this paper, loss given default is calculated as the percentage shortfall of assets below debt,

$$(5) \quad LGD_{it} = \frac{D_{it}^d - (1-h)A_{it}^d}{D_{it}^d},$$

where LGD_{it} is the loss given default for a defaulting farm i at the time of default t , A_{it}^d and D_{it}^d are the values of farm assets and debt, respectively, of a defaulting farm at the time of default, and h is the percent recovery cost for assets in default. The average loss given default for a portfolio, LGD , is calculated as the weighted average of the loss given default for defaulting farms, with weights being the debt in default.

The expected loss is the probability of default PD times the loss given default LGD , expressed as a percent of the total debt of the portfolio. The dollar value for the expected loss per farm equals the percent expected loss times the value of farm debt, called exposure at default EAD ,

$$(6) \quad EL = (PD)(LGD)(EAD).$$

Given that default is a binary variable, the average standard deviation of default SD for a farm is

$$(7) \quad SD = \sqrt{PD(1 - PD)}.$$

The standard deviation of default for a portfolio of farms is

$$(8) \quad SD_p = SD \sqrt{\sum_{i=1}^N \sum_{j=1}^N w_i w_j \rho_{ij}},$$

where w_i is the weight of farm i in the portfolio and ρ_{ij} is the default correlation between farm i and farm j . Because the default correlation between two farms cannot be directly measured (as it would require repeated default observations over time), default correlations are often approximated by asset return correlations (Crouhy, Galai, and Mark). The farms in the portfolio are assumed to have a uniform distribution with an average weight of $w_i = 1/N$, where N is the number of farms in the portfolio. Assuming a uniform distribution, equation (8) can be further simplified as

$$(9) \quad SD_p = SD \sqrt{N(1/N)^2 + 2(N(N-1)/2)(1/N)^2 \rho} = SD \sqrt{\rho + (1 - \rho)/N},$$

where ρ is the average asset return correlation between farms. With similar exposure to all farms in the portfolio, portfolio risk depends on the number of farms in the portfolio N and the asset return correlations between farms ρ .

Equation (9) is presented graphically in figure 2. The volatility of portfolio defaults is due to three factors: number of assets, concentration and correlation (Garside, Stott, and Stevens). Concentration refers to the relative proportion of debt for each farm in the credit portfolio. In this study, the value of debt for the most indebted farm in the sample does not exceed 2% of the value of total debt for the portfolio of farms. For such a portfolio with similar debt proportions, concentration risk is diversified away as the number of borrowers in the portfolio increases, i.e. $SD_p \rightarrow SD\sqrt{\rho}$ as $N \rightarrow \infty$.

Correlation describes the sensitivity of the portfolio to common fundamental factors. In large portfolios, systematic risk due to correlation dominates concentration risk. As a numerical example, it follows from equation (9) that if the asset return correlation is 10%, the volatility of default for a large portfolio of, say, 2,000 borrowers is about 30% of the average farm volatility of default.

The unexpected loss is calculated from the tails of the credit risk distribution by determining a level of loss, $UL(\alpha)$, which will be exceeded with a specified probability α . The probability α reflects the risk tolerance of the lender. The unexpected loss (expressed as a percent of the total debt in the portfolio) is the product of the critical value associated with a probability α , $N^{-1}(\alpha)$, the standard deviation of default for the portfolio, and the loss given default.³ The dollar value for the unexpected loss per farm equals the percent unexpected loss times the exposure at default (the value of farm debt),

$$(10) \quad UL(\alpha) = N^{-1}(\alpha) (SD_p)(LGD)(EAD).$$

Credit risk is defined using the concepts of expected loss, EL , and unexpected loss, UL . The expected loss represents an average historical loss due to the average default rate (equation (6)) and is regarded as an anticipated cost of doing business. It is represented by the allowance for loan losses on the lender's balance sheet and is often included as a cost in loan pricing. On the other hand, the unexpected loss represents a maximum loss at a desired solvency rate (equation (10)). The unexpected loss at the portfolio level reflects the volatility of default over time mainly due to correlation among farms in the portfolio. Economic capital is needed to cover unexpected losses $UL(\alpha)$ which will be exceeded with a probability α . Credit value-at-risk, $VaR(1-\alpha)$, is the sum of the expected loss and the unexpected loss,

$$(11) \quad VaR(1-\alpha) = EL + UL(\alpha).$$

The credit VaR represents the total loss that will be exceeded with probability α and therefore the needed total capital to backstop credit risk at a desired solvency rate $(1-\alpha)$.

Asset Return Correlation Model

Asset return correlations are used in calculating portfolio risk (equation (9)) and unexpected loss (equation (10)). Higher correlations among farm performances will lead to higher unexpected losses. Instead of calculating correlations between asset returns for individual borrowers, credit risk studies use factor models (Crouhy, Galai, and Mark). Correlations calculated from factor models are associated with lower sampling errors than individual asset return correlations and significantly reduce the number of correlations that need to be calculated (Crouhy, Galai, and Mark).⁴ A factor model imposes a structure on the asset return correlations and links them to one or more fundamental factors,

$$(12) \quad r_{it} = \alpha_i + \beta_i r_{mt} + e_i, \text{ for } i = 1 \dots N,$$

where r_{it} is the asset return for farm i at time t , r_{mt} is the asset return at time t for the average "market" farm which in this study represents the fundamental factor, α_i and β_i are the coefficients to be estimated, and e_i is the idiosyncratic risk factor which is not correlated with the fundamental factor or with the idiosyncratic risk factors of other farms. Using statistics

³ Using the normal distribution, the critical values, $N^{-1}(\alpha)$, are 1.64, 2.33, and 2.58 at the 95%, 99%, and 99.5% confidence levels, respectively. Larger financial institutions tend to use a solvency rate of 99.97% reflecting a goal of an AA rating for the Standard & Poor's methodology where the mean default rate is 0.03%.

⁴ For a portfolio with 1000 borrowers ($N=1000$), the number of different correlations to estimate is $N(N-1)/2 = 499,500$. Using a factor model with K factors (in the single index model used in this paper, $K=1$), the number of parameters to be estimated is $KN + K(K-1)/2 = 1000$.

formulas, the variance of individual asset returns $\text{var}(r_{it})$, the covariance of asset returns $\text{cov}(r_{it}, r_{jt})$, and correlation of asset returns among farms ρ_{ij} can be represented as

$$(13) \quad \text{var}(r_{it}) \equiv \sigma_i^2 = \beta_i^2 \text{var}(r_{mt}) + \text{var}(e_i),$$

$$(14) \quad \text{cov}(r_{it}, r_{jt}) \equiv \sigma_{ij} = \beta_i \beta_j \text{var}(r_{mt}), \text{ and}$$

$$(15) \quad \rho_{ij} = \sigma_{ij} / \sigma_i \sigma_j = \beta_i \beta_j \text{var}(r_{mt}) / [\text{stdev}(r_{it}) * \text{stdev}(r_{jt})].$$

In other words, a factor model represents the correlation among asset returns as the covariance of asset returns calculated from the factor model divided by the product of the individual standard deviations of the farm asset returns. The average correlation is calculated as the average of the individual correlations and used in equation (9).

Two Applied Credit Risk Models

This paper considers credit value-at-risk methodologies utilized by two vendor models. CreditMetrics was developed by J.P. Morgan and the KMV model was developed by the KMV Corporation, now called Moody's KMV. Both models use Merton's asset value model and further classify borrowers into several credit quality classes. The advantage of using credit quality classes is that the grouping of homogenous borrowers (called granularity) allows for more precise estimates of the probability of default and loss given default. The disadvantages of using credit quality classes are that the precision of assigning borrowers into different credit quality classes is lower and that a large number of observations is needed to obtain statistically valid results.

CreditMetrics and the KMV model make different simplifying assumptions regarding their credit quality classes. Unlike CreditMetrics which uses data from rating agencies with established credit quality classes, KMV uses endogenous models to group borrowers. CreditMetrics follows a mark-to-market credit migration approach and is based on migration between credit quality classes over time.⁵ The KMV is based on distance-to-default measures and expected default frequencies.

The CreditMetrics Model

CreditMetrics extends Merton's model to include changes in credit quality. The CreditMetrics model is based on a credit migration analysis reflecting the migration of borrowers from one credit quality to another credit quality or to default within a given time horizon. The model uses a credit rating system, with credit quality classes, and a transition matrix reflecting the probabilities of migrating from one credit quality class to another class over time. The rating system and transition matrix are either provided by rating agencies such as Moody's and Standard & Poor's or developed by some large financial institutions using their own historical records. Because farms are not traded and are not rated by rating agencies, agricultural banks usually use a credit scoring approach to assign borrowers to credit quality classes (Splett et al.). In this paper, a credit scoring approach is used to assign farmers into credit quality classes and to estimate a transition matrix reflecting the probabilities of migration between credit quality

⁵ The CreditMetrics approach in this study utilizes the migration concept but does not extend to the market value of non-tradable farm debt. In other words, as mentioned earlier, this study follows the loss-based method rather than the NPV-based method to analyze credit risk.

classes over time (Barry, Escalante, and Ellinger). The analysis of Barry, Escalante, and Ellinger is extended by assigning farms to a default class if the value of their debt exceeds the value of their assets. The probability of default for every credit quality class is calculated as the probability of moving from the current credit quality class to the worst credit quality class, default. Loss given default and expected and unexpected loss are calculated for every credit quality class.

The KMV Model

The KMV model first derives a probability of default for every borrower and then groups borrowers into credit quality classes based on their derived probability of default. Using Merton's model, the default process in the KMV model is assumed endogenous and occurs when the value of farm assets falls below the value of farm debt.⁶

A distance-to-default index, DD_{it} , is calculated as the number of standard deviations between the mean of the distribution of the asset value and the debt value,

$$(16) \quad DD_{it} = \frac{A_{it} - D_{it}}{\sigma_i^A},$$

where σ_i^A is the standard deviation of assets. Although the true values of farm assets change continuously over time, the asset values are measured discretely; hence, equation (16) is a discrete version of equation (4) (Crouhy, Galai, and Mark). Borrowers are grouped into several credit quality classes based on their distance to default. The probability of default (which is also called an expected default frequency) can be measured either as the statistical probability of default using the normal distribution or as the historical default rate for each credit quality class. Loss given default and the expected and unexpected loss are calculated for every credit quality class.

Data

Few lenders have reasonable time-series cross-sectional data on their borrowers' loan performance and underwriting variables to be able to estimate credit risk models. Most lenders have to match their borrower data with external sources such as rating agencies data and stock and bond market data. In agriculture, data histories are short, claims on farms are not traded or rated by rating agencies, and the borrowers' financial data are seldom updated on real estate loans. Alternative data sources, thus, are needed to estimate probabilities of default and loss given default. In this case, data from farm records (e.g. measures from balance sheets, income statements and cash flows) can be used to develop benchmark measures for credit risk models. Farm data for a given state or region are useful because a regional agricultural bank or a FCS institution would have borrowers with similar farm typology and characteristics.

Farm-level data are obtained from the Illinois Farm Business Farm Management (FBFM) Association for 1995-2002. Consistent with Ellinger et al., only farms with asset values of at least \$40,000 and gross farm returns of least \$40,000 are included in the analysis. Farms with no

⁶ The KMV has observed from a sample of corporate firms that actual default occurs when the value of assets reaches approximately the value of short-term debt plus half of the value for long-term debt. If the KMV definition of default is used, the distance to default will be higher, and therefore, the capital requirements lower. This study follows the more conservative Merton's definition of default.

debt are excluded from the analysis as they will not be included in a lender's portfolio. About 2,000 farm operators are included in the data annually for the 8 years, which leads to 16,049 farm observations. All these observations are used in subsequent analyses except when a specific condition requires a restriction in the sample size (these conditions will be discussed later).

Farms in default are defined as those with debt-to-asset ratios greater than one.⁷ There are 91 farms in default for 1995-2002. Compared to less leveraged groups of farms, farms in default are clearly in an unfavorable financial condition: they have the lowest net farm income of \$14,802 and the lowest net worth of -\$119,055 (table 1). Ellinger et al. found similar results.

The average farm has \$1,054,499 in farm assets and \$303,859 in farm debt (table 1).⁸ A debt-to-asset ratio for the average farm of 32.84% is calculated as the average debt-to-asset ratios across farms and over time.⁹ Figure 3 shows that the debt-to-asset ratio varied over the years, with the highest ratio occurring in 2001. The average standard deviation of assets was \$148,437, calculated as the standard deviation for each farm then averaged across all farms. In agriculture, the variability in asset values is mostly due to variability in real estate values and agricultural income but it also includes deterministic changes such as acquisitions of real estate or machinery (often financed with deterministic changes in debt). Including both random changes in asset prices and changes in the levels of asset holdings is important because these are the sources of changes in asset values observed by lenders in their credit risk assessments. The variability of farm assets is used to calculate distance-to-default measures for each farm.

Results for the Portfolio of All Farms

The average probability of default was calculated as the statistical probability of default and as the historical default rate. A statistical probability of default was calculated for each farm using the properties of the normal distribution and the farm values for assets, debt, and standard deviation of assets. An average statistical probability of default of 2.474% was calculated as the weighted average of the probability of default for all farms, weighted by the debt for each farm (table 2). Because the statistical probability of default often differs from the actual historical default rate, credit risk studies often use the latter measure (Crouhy, Galai, and Mark). A historical default rate of 0.567% was calculated as the percent farms in default, which equals 91 farms in default divided by 16,049 farm observations. Lenders, however, prefer to calculate the default rate as the percent debt in default (or the proportion of defaulted farms, weighted by farm debt), leading to a historical default rate of 0.785%. In figure 4, these default rates are calculated for every year in this study.

The loss given default was calculated for each defaulting farm as the percentage shortfall of recovered assets below debt using equation (5). An average loss given default of 35.458% was calculated as a weighted average loss given default for defaulting farms, with weights being

⁷ In practice, default could be defined by other values of debt-to-asset ratios, reflecting lenders' perceptions of borrower viability and the costs of foreclosure. A sensitivity analysis is presented in a later section.

⁸ In this study, the total liabilities of a farm are referred to as debt.

⁹ The average values of assets and debt imply a debt-to-asset ratio that differs from the average of the debt-to-asset ratios.

the debt in default (table 2).¹⁰ In other words, on average 35.458% of the debt value is lost when a farm defaults. A 10% recovery cost for assets in default was assumed in the calculations of loss given default, based on Featherstone and Boessen, and Featherstone et al. These recovery costs include legal, personnel, property tax, title fees, advertising and other acquisition fees, and the time value of money (Featherstone and Boessen). The value of debt used to calculate loss given default includes the accrued interest on debt and the estimated accrued tax liability for real estate.

Instead of calculating the average loss given default across all years, the average loss given default can also be calculated for each year in the study. The median, first and third quartiles of loss given default were calculated for every year based on the loss given default for individual farms defaulting in that year. Figure 5 shows the average, median, and first and third quartiles of loss given default for 1995-2002. The average loss given default was highest in 2001, similarly to the debt-to-asset statistics.

The expected loss was calculated as the historical (or statistical) default rate times the loss given default. Expected losses are 0.278% and 0.877% of the total debt in the portfolio, calculated using the historical and statistical default rates, respectively. When these percentages are multiplied by the average farm debt, the expected losses are \$846 and \$2,666 per farm using the historical and statistical default rates, respectively (table 2).

An estimate of the correlation of asset returns is needed to determine portfolio risk and unexpected loss. Following the theoretical model expressed in equation (1), asset returns are defined as the logarithm of end-year assets to beginning-year assets.¹¹ Only farm records with 8 years of continuous data are used to calculate asset return correlations among farms in the portfolio. Therefore, the sample size was restricted from about 2,000 farms a year to 321 farms a year (or $8 \times 321 = 2,568$ farm observations). The restriction of sample size was needed to produce a reliable estimate for the asset return correlation, however, a survivorship bias was also introduced because farms that default and exit farming will not be included in the analysis.

Although, in theory, asset return correlations can be calculated by taking correlations among all farms, such procedures are very computationally intensive. Instead, credit risk studies use factor models to calculate these correlations. Annual asset returns were calculated for the average or “market” farm, by averaging asset returns of the 321 farms for each year. A single factor model was estimated by regressing the time-series of asset returns for each farm on the time-series of asset returns for the average farm, producing 321 equations to be estimated. The β coefficients in the factor model, thus, measure the systematic risk of individual farms as related to the risk of the average “market” farm. These β coefficients range from -4.91 to 10.24 with a mean of 1 (by identity) and a standard deviation of 1.6. Correlations among asset returns were calculated as the covariance of asset returns calculated from the factor model divided by the product of the individual standard deviations of the farm asset returns, according to equation (15). An average correlation of 10.05% was calculated by averaging correlations among all farms.

Using equation (7), the standard deviation of default for a farm was calculated as 8.827% and 15.534% using the historical and statistical default rates, respectively (table 2). Using

¹⁰ Since loss given default is calculated only for defaulting farms, the sample size for this calculation is the 91 farms in default.

¹¹ If asset returns are expressed as the percent change from beginning-year assets to end-year assets, the results remain similar.

equation (9), the standard deviation of default for the portfolio was calculated as 2.799% and 4.926% of the debt in the portfolio, using the historical and statistical default rates, respectively (table 2). The relatively low correlation (10.05%) still implies a substantial reduction in portfolio risk of about 30% relative to the average stand-alone risks in the portfolio.

Portfolio risk and loss given default determine the level of unexpected losses, based on a given risk tolerance. The unexpected losses were calculated using equation (10). Table 2 shows unexpected losses of 2.313% (\$7,027 per farm) and 4.07% (\$12,366 per farm) using the historical and statistical default rates, respectively, which will be exceeded with $\alpha=1\%$ probability. Agricultural lenders can achieve a desired solvency rate of $(1-\alpha) = 99\%$ by holding economic capital equal to the unexpected losses calculated above. Higher solvency rates $(1-\alpha)$ are associated with higher levels of unexpected losses (and thus higher level of needed economic capital). Figure 6 graphically shows the values of expected loss and the unexpected loss if they are based on annual data. The figure shows a considerable variation across years and demonstrates the importance of calculating expected and unexpected loss using longer time-series data.

The value-at-risk, VaR (99%) was calculated as the sum of expected and unexpected loss according to equation (11). The VaR (99%) represents a total capital of 2.591% of the total debt in the portfolio (or \$7,873 per farm) and 4.947% of the total debt in the portfolio (or \$15,032 per farm) using the historical and statistical default rates, respectively (table 2). This total capital is needed to protect against both expected and unexpected losses at a 99% solvency rate.¹²

Sensitivity Analyses

This section describes the sensitivity analyses based on different assumptions about the definition of default, the distribution of farms in the portfolio, and the correlation among asset returns.

Definition of Default

The models considered in this study assumed Merton's definition of default, i.e. default occurs when the value of debt exceeds the value of assets. Under collateral based lending, however, default occurs when the loan value falls below the collateral value even if the borrower still has some equity. To test the robustness of previous results, default is now assumed to occur when debt exceeds 90% of the assets (while still assuming a 10% recovery cost for assets in default). The number of defaults increases to 170 farm observations and the probability of default increases to 1.642% of the debt in the portfolio (table 3).¹³ The loss given default, however, drops to 18.761% of the debt value for defaulting farms. The reason for the lower loss given default is that more farms are defaulting but they do so at a lower (90%) level of indebtedness. The expected loss is 0.308% of the debt in the portfolio or \$936 per farm, the unexpected loss at the 99% solvency rate is 1.761% or \$5,352 per farm, and the total loss or VaR at the 99% solvency rate is 2.069% or \$6,288 per farm (table 3). These results are similar to the

¹² Berkowitz and O'Brien examined the accuracy of the VaR models by comparing the VaR forecasts with actual data on credit risk losses. They found that the VaR estimates tend to be conservative relative to the respective percentile of actual losses.

¹³ The rest of the analyses in this paper use the historical default rate although the statistical probability of default can also be used.

results in the basic case and demonstrate that the Merton's definition of default is a reasonable assumption.

Distribution of Farms in the Portfolio

The correlation analysis assumed that farms are distributed uniformly in the lender's portfolio with an average weight of $w_i = 1/N$. The assumption of uniform distribution lead to the simplification of equation (8) to equation (9), where the average correlation was calculated as the simple average of the correlations among farms. Instead of assuming a uniform distribution, equation (8) can be estimated using the actual farm weights, $w_i = D_i / \sum_{i=1}^N D_i$, which are the debt of each farm as a proportion of the total debt in the portfolio. A weighted average correlation of 10.58% is very similar to the simple average correlation of 10.05% (table 3). Therefore, these results show that assuming a uniform distribution of farms is reasonable. Although, from a farmer's perspective, farms differ considerably with respect to their debt values, from a lender's perspective, the value of debt for the most indebted farm in the portfolio did not exceed 2% of the total debt in the portfolio. Since agricultural lenders usually do not collect updated financial information if the loans are performing as dictated in the loan contract, correlations can be very challenging to calculate using only internal loan origination data. This study shows that if farmer-borrower data is matched with external farmer data, correlations can be calculated assuming a uniform distribution for these farms.

Correlation

An important strength of the methodology used in this paper is the consideration of the correlations among farm performances. While the expected losses are the same as the basic case, assuming that correlations are zero or one can have significant consequences for the necessary economic capital (unexpected losses). The unexpected losses at the 99% solvency rate are 0.058% or \$175 per farm for $\rho=0$, 2.313% or \$7,027 per farm for $\rho=10.05\%$ (the actual case), and 7.293% or \$22,160 per farm for $\rho=1$ (table 3). Thus, assuming zero correlations would lead to an undercapitalization of \$6,852 per farm while assuming correlations of one would lead to an overcapitalization of \$15,133 per farm in achieving a 99% solvency rate for a financial institution. These differences in required capital are significant and demonstrate the importance of incorporating correlations into credit risk models.

Results for the CreditMetrics and KMV Models

The results presented so far showed expected and unexpected losses for the sample of all farms. Agricultural lenders, however, emphasize granularity, i.e. the grouping of homogenous borrowers into credit classes, and seek to calculate capital needs for each class. Borrowers are grouped into credit classes based on their farm credit values for the CreditMetrics model and their distance-to-default for the KMV model. After these classes are determined and the probability of default is calculated, the calculations of expected and unexpected losses for each class follow the previously presented methodology.

The CreditMetrics model is based on migration analysis, where farmers migrate from one credit quality class to another credit quality class next year. Only farms with records available for two consecutive years were included in the migration analysis which reduced the sample size to 9,834 observations for 1995-2002. Credit quality classes were based on credit scoring values, consistent with banks' current evaluation practices for farmers' credit worthiness (Splett et al.).

Five credit score classes were formed based on weighted measures of liquidity, solvency, profitability, repayment capacity, and financial efficiency (for more detail, see Splett et al.). The migration analysis in Barry, Escalante, and Ellinger is extended by adding a default class for farms with debt-to-asset ratio greater than 1. A migration matrix was estimated showing the migration of farmers from one credit quality class to another credit quality or default next year (table 4). The probability of default was calculated as the debt value for defaulted farms over the debt value for all farms starting in a given credit class. The results show that farms starting in credit class 1 have a probability of default of 0%, while farms starting in the worst credit class 5 have a probability of default of 0.96% (table 4). These estimates of the probability of default were repeated in table 5 and used in the calculations of expected and unexpected loss for each credit class following the previously presented methodology. Table 5 shows the probability of default, loss given default, and the expected and unexpected loss by credit score class. The expected loss ranges from 0% of the portfolio debt for the best credit quality class to 0.428% for the worst credit quality class. The unexpected loss ranges from 0% of the portfolio debt for the best credit quality class to 3.226% for the worst credit quality class.

The KMV model is based on distance-to-default measures which reflect how far a farm is away from default, in other words, how many standard deviations assets are above debt (equation (16)). The farmers were grouped in classes based on their distances to default. In this study, groups are formed based on whether a farm is less than 0.1, between 0.1 and 1, between 1 and 2, and more than 2 standard deviations away from default.¹⁴ After the farms are classified based on their distances to default, the probability of default, loss given default, and the expected and unexpected loss are calculated for each distance-to-default class following the previous presented methodology. Farms that are at least 2 standard deviations away from default have a probability of default of 0.085% while farms that are less than 0.1 standard deviations away from default have a probability of default of 7.72% (table 6). The expected loss ranges from 0.02% for the best credit quality class to 3.017% for the worst credit quality class. The unexpected loss ranges from 0.516% for the best credit quality class to 7.736% for the worst credit quality class.

Summary and Conclusions

In this paper, credit risk models and farm-level data were used to estimate economic capital needed to protect against unexpected losses and allowances for losses needed to cover expected losses for agricultural lenders under the New Basel Capital Accord. The theoretical models combined Merton's option pricing approach and credit value-at-risk methodologies. These models are estimated for the portfolio of farms and then by grouping farms into different credit quality classes using CreditMetrics and the KMV.

Using farm financial data from Illinois, the expected losses on farm debt were calculated as 0.785% and 2.474% using the historical default rate and the statistical probability of default, respectively. The unexpected losses, which together with the expected losses will be exceeded with a 1% probability, were calculated as 2.313% and 4.07% using the historical default rate and the statistical probability of default. Sensitivity analyses were performed with different assumptions about the default definition, the distribution of farms, and the correlation among farm asset returns. Finally, the results from CreditMetrics and KMV models show that probabilities of default and expected and unexpected losses vary considerably from class to class. An important goal of the New Basel Accord is to increase the granularity of the risk ratings and

¹⁴ The New Basel Accord does not set the thresholds for these classes, therefore, financial institutions or other studies can pick their own thresholds for the distances-to-default classes.

to more closely relate these ratings and risk measures to the economic capital needs of financial institutions. Agricultural lenders could also extend the analysis presented in this paper to address capital needs for operating versus real estate loans by calculating default rates and loss given default for the two types of loans.

The New Basel Accord and the modern approaches to the measurement, modeling, and management of credit risks allow financial institutions to determine capital requirements based on the riskiness of their loan portfolios. However, most agricultural lenders lack a sufficient history of longitudinal borrower data. Long data histories are crucial because farm financial performance and correlation among farms vary over business cycles. Agricultural lenders can also match their borrower data with other existing databases of farmers based on geographical location and farm typology. At present, it is likely that historic series of farm-level data are easier to compile by universities or the government and are more readily available than loan-level performance data. Several high quality databases of farm-level data, such as the Agricultural and Resource Management Study data compiled by USDA, the Kansas State University farm record system, and the Illinois FBFM data used in this study, already exist and are used extensively for research analyses. Better data record gathering and keeping and evaluation of the riskiness of the loan portfolio will result in better estimation of the solvency of financial institutions. Over time, it is anticipated that larger institutions can compile more comprehensive data histories, although their risk measures will still need to be compared to those of peer institutions, rating agencies, and business performance systems.

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Table 1. Descriptive Statistics

Debt-to-Asset Groups	Number of Farm Obs.	Net Farm Income	Net Worth	Assets	Debt
$D/A \leq 0.2$	5,192	\$51,503	\$1,123,387	\$1,240,690	\$117,303
$0.2 < D/A \leq 0.4$	5,299	\$45,118	\$762,359	\$1,082,577	\$320,218
$0.4 < D/A \leq 0.7$	4,745	\$34,699	\$441,169	\$903,577	\$462,408
$0.7 < D/A \leq 1$	722	\$16,796	\$127,626	\$596,235	\$468,609
$D/A > 1^a$	91	\$14,802	-\$119,055	\$301,824	\$420,879
All Farms ^b	16,049	\$42,657	\$750,640	\$1,054,499	\$303,859

Notes: ^a Farms with $D/A > 1$ are farms in default.

^b The last row represents results for the average farm.

Table 2. Expected and Unexpected Losses for the Portfolio of Farms

	Using Historical Default Rate	Using Statistical Probability of Default
Probability of Default	0.785%	2.474%
Loss Given Default	35.458%	35.458%
Asset Return Correlation	10.050%	10.050%
St. Dev. of Default for a Farm	8.827%	15.534%
St. Dev. of Default for the Portfolio	2.799%	4.926%
Expected Loss ^a	0.278%	0.877%
	\$846	\$2,666
Unexpected Loss (5%) ^b	1.628%	2.865%
	\$4,946	\$8,704
Unexpected Loss (1%) ^b	2.313%	4.070%
	\$7,027	\$12,366
Unexpected Loss (0.5%) ^b	2.561%	4.506%
	\$7,781	\$13,693
Value-at-Risk (95%) ^c	1.906%	3.742%
	\$5,792	\$11,370
Value-at-Risk (99%) ^c	2.591%	4.947%
	\$7,873	\$15,032
Value-at-Risk (99.5%) ^c	2.839%	5.384%
	\$8,627	\$16,359
Number of Farms in Default	91	91
Number of Farm Observations	16,049	16,049

Notes: ^a Losses are expressed as a percent of the total debt in the portfolio and as a dollar value per farm.

^b The unexpected losses will exceed $UL(\alpha)$ with a probability α .

^c Value-at-Risk (VaR) is the sum of expected and unexpected losses. The $VaR(1-\alpha)$ represents the total capital needed to protect against both expected and unexpected losses at a $(1-\alpha)$ solvency rate.

Table 3. Sensitivity Analyses

	Basic Model ^a	Default if debt > 0.9*assets	Actual farm weights	Correl = 0	Correl = 1
Prob. of Default	0.785%	1.642%	0.785%	0.785%	0.785%
Loss Given Default	35.458%	18.761%	35.458%	35.458%	35.458%
Asset Return Correlation	10.050%	10.050%	10.580%	0.000%	100.000%
St. Dev. of Default for a Farm	8.827%	12.707%	8.827%	8.827%	8.827%
St. Dev. of Default for the Portfolio	2.799%	4.029%	2.871%	0.070%	8.827%
Expected Loss ^b	0.278%	0.308%	0.278%	0.278%	0.278%
	\$846	\$936	\$846	\$846	\$846
Unexpected Loss (5%) ^c	1.628%	1.240%	1.670%	0.041%	5.133%
	\$4,946	\$3,767	\$5,073	\$123	\$15,598
Unexpected Loss (1%) ^c	2.313%	1.761%	2.372%	0.058%	7.293%
	\$7,027	\$5,352	\$7,208	\$175	\$22,160
Unexpected Loss (0.5%) ^c	2.561%	1.950%	2.627%	0.064%	8.075%
	\$7,781	\$5,926	\$7,981	\$194	\$24,538
Value-at-Risk (95%) ^d	1.906%	1.548%	1.948%	0.319%	5.412%
	\$5,792	\$4,703	\$5,920	\$969	\$16,444
Value-at-Risk (99%) ^d	2.591%	2.069%	2.651%	0.336%	7.571%
	\$7,873	\$6,288	\$8,054	\$1,021	\$23,006
Value-at-Risk (99.5%) ^d	2.839%	2.258%	2.905%	0.342%	8.354%
	\$8,627	\$6,862	\$8,828	\$1,040	\$25,384
No. Farms in Default	91	170	91	91	91
No. of Farm Obs.	16,049	16,049	16,049	16,049	16,049

Notes: ^a The basic model is the same as the model using the historical default rate in table 2.

^b Losses are expressed as a percent of the total debt in the portfolio and as a dollar value per farm.

^c The unexpected losses will exceed $UL(\alpha)$ with a probability α .

^d Value-at-Risk (VaR) is the sum of expected and unexpected losses. The $VaR(1-\alpha)$ represents the total capital needed to protect against both expected and unexpected losses at a $(1-\alpha)$ solvency rate.

Table 4. Credit Score Migration Matrix (Used in the CreditMetrics Model) ^{a, b}

Current Year Credit Score	Credit Rating Next Year						No. of Farm Obs.	No. of Farms in Default
	Class 1	Class 2	Class 3	Class 4	Class 5	Default		
Class 1	54.70%	28.78%	12.39%	3.66%	0.46%	0.00%	2,732	0
Class 2	10.53%	41.01%	30.61%	13.83%	3.99%	0.03%	2,349	1
Class 3	3.14%	17.98%	38.95%	24.49%	15.03%	0.42%	2,444	9
Class 4	1.17%	12.51%	28.89%	32.88%	23.67%	0.89%	1,429	9
Class 5	0.07%	4.05%	20.48%	22.02%	52.42%	0.96%	880	10

Notes: ^a Classes are defined based on credit score values.

^b The migration matrix shows the probabilities of migrating from class i in year t to class j or default in year $(t+1)$.

Table 5. The CreditMetrics Model

Credit Score Classes ^a	No. of Farm Obs.	No. of Farms in Default	Prob. of Default ^b	Loss Given Default	Expected Loss ^c	Unexpected Loss (1%) ^{c,d}	VaR (99%) ^e
Class 1	2,732	0	0.000%	-	0.000%	0.000%	0.000%
Class 2	2,349	1	0.030%	50.700%	0.015%	0.655%	0.671%
Class 3	2,444	9	0.421%	15.689%	0.066%	0.752%	0.818%
Class 4	1,429	9	0.888%	15.497%	0.138%	1.077%	1.215%
Class 5	880	10	0.960%	44.565%	0.428%	3.226%	3.654%

Notes: ^a Each farm is assigned into a class based on the value of its credit score.

^b The probability of default comes from the migration analysis in table 4.

^c Losses are expressed as a percent of the total debt in the portfolio.

^d The unexpected losses will exceed $UL(\alpha)$ with a probability α .

^e Value-at-Risk (VaR) is the sum of expected and unexpected losses. The $VaR(1-\alpha)$ represents the total capital needed to protect against both expected and unexpected losses at a $(1-\alpha)$ solvency rate.

Table 6. The KMV Model

Distance-to-Default Classes ^a	No. of Farm Obs.	No. of Farms in Default	Prob. of Default	Loss Given Default	Expected Loss ^b	Unexpected Loss (1%) ^{b,c}	VaR (99%) ^d
$DD > 2$	12,545	3	0.085%	23.990%	0.020%	0.516%	0.536%
$1 < DD \leq 2$	1,608	5	0.340%	51.640%	0.176%	2.228%	2.403%
$0.1 < DD \leq 1$	802	12	2.524%	20.760%	0.524%	2.419%	2.943%
$DD \leq 0.1$	1,094	71	7.720%	39.080%	3.017%	7.736%	10.753%

Notes: ^a Each farm is assigned into a class based on its value of distance-to-default.

^b Losses are expressed as a percent of the total debt in the portfolio.

^c The unexpected losses will exceed $UL(\alpha)$ with a probability α .

^d Value-at-Risk (VaR) is the sum of expected and unexpected losses. The $VaR(1-\alpha)$ represents the total capital needed to protect against both expected and unexpected losses at a $(1-\alpha)$ solvency rate.

Figure 1. Probability Distribution of Asset Values and Distance-to-Default

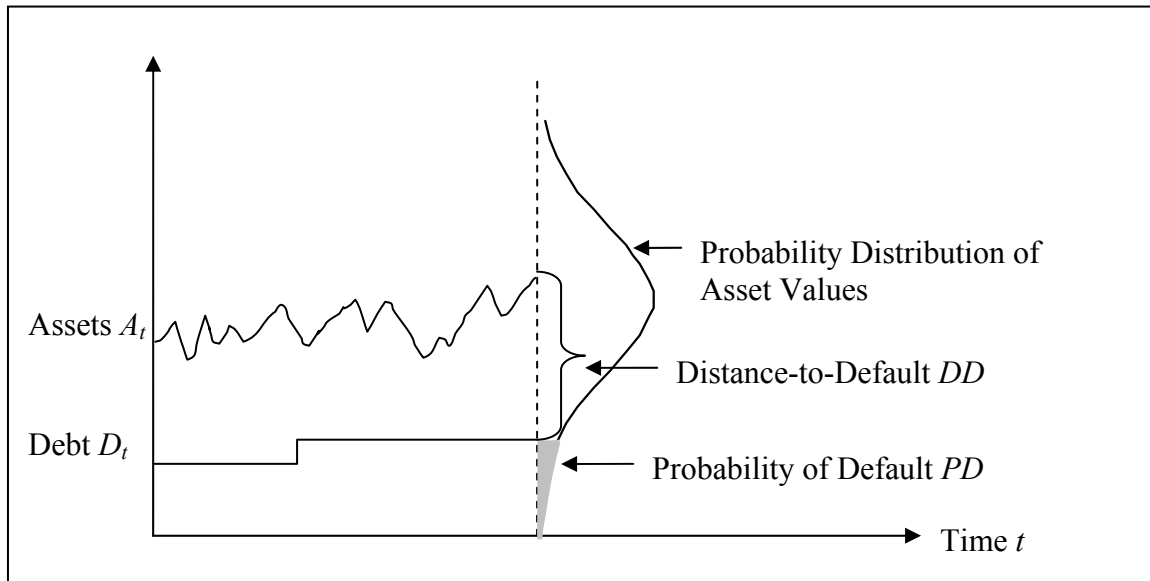
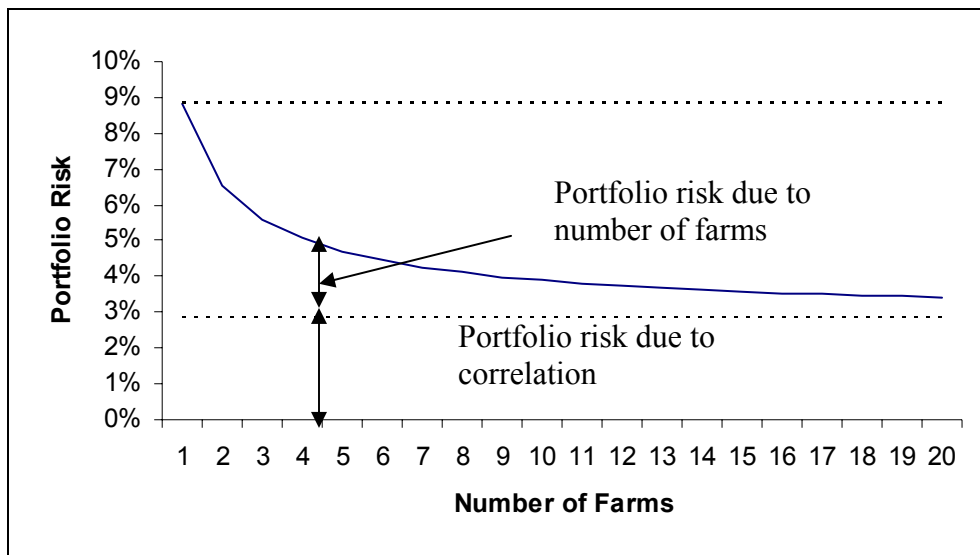


Figure 2. Effects of Number of Farms and Correlation on Portfolio Risk



Portfolio risk is the standard deviation of default for a portfolio of farms. Portfolio risk is a function of the number of farms in the portfolio and the asset return correlation among farms.

Figure 3. Average Farm Debt and Assets and Debt-to-Asset Ratios

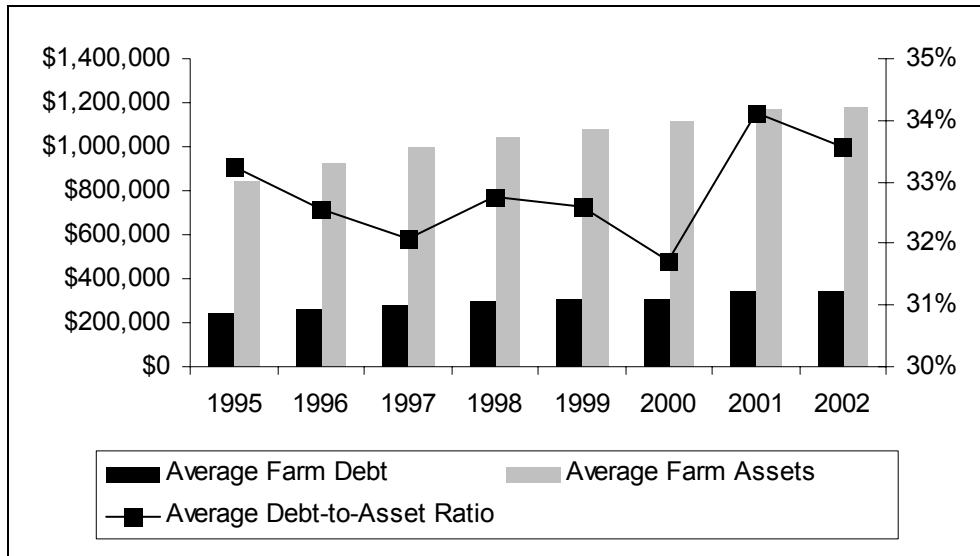


Figure 4. Default Rates

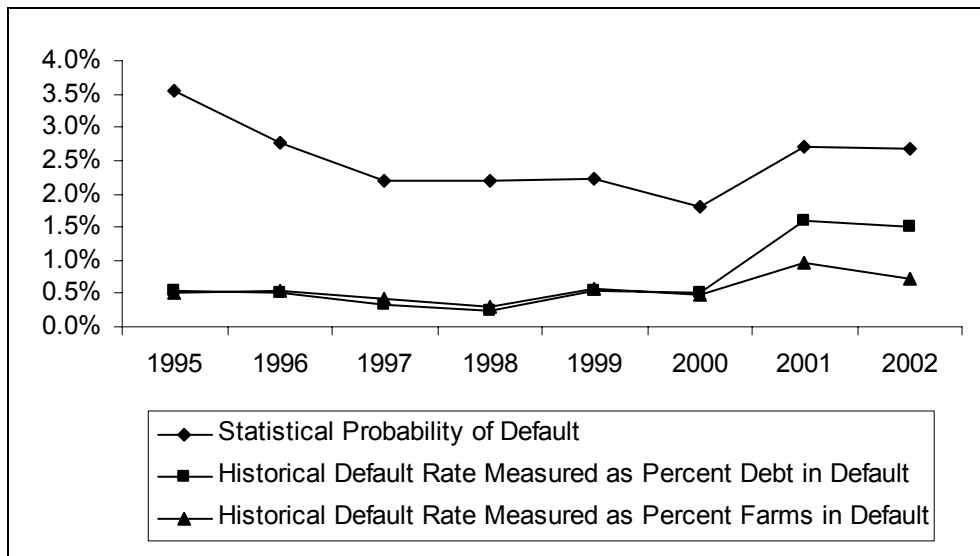


Figure 5. Loss Given Default for Farm Debt

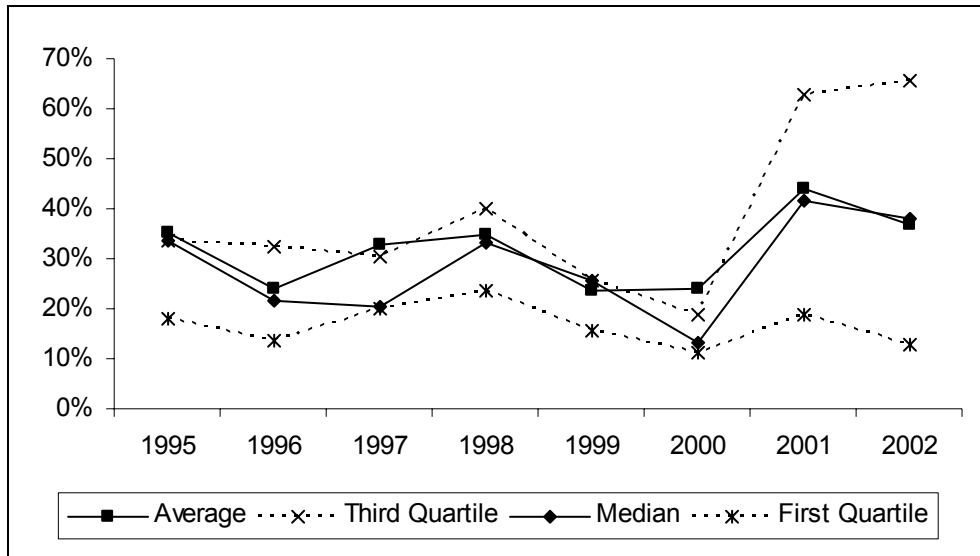


Figure 6. Expected and Unexpected Losses

