Credit Risk Models and Agricultural Lending

Ani L. Katchova and Peter J. Barry

Credit risk models are developed and used to estimate capital requirements for agricultural lenders under the New Basel Capital Accord. The study uses credit value-at-risk methods to calculate probability of default, loss given default, and expected and unexpected losses. Two applied models, CreditMetrics and Moody's KMV, are estimated using farm financial data. The results show that the necessary capital for agricultural lenders under the New Basel Accord varies substantially depending on the riskiness and granularity of the portfolio.

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

Recent advancements in measuring and managing credit risk emphasize using frequency and severity of loan defaults 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's best practice and offer institutions a range of ways 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. Reducing unneeded capital holdings (if the results show excessive capital) would free funds for 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 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 nonloss 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 that influence capital requirements. Agriculture has a lengthy production cycle, which often leads to less frequent, seasonal payments of loans (Barry). Agriculture is also capital intensive with 87% of the total assets consisting of farm real estate and machinery, according to USDA statistics for 2002. Financial performance of farms can be highly correlated, especially for farms in the same geographic region. 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 study 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 study adapts and applies credit risk models available in the finance field to fit the unique characteristics of agricultural lending. The credit risk models here are based on Merton's option pricing

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[1] Alternative approaches include using 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).

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approach and credit value-at-risk methods. The models will be estimated for the portfolio of all farms using data from the Illinois Farm Business Farm Management (FBFM) association and also by grouping farms into different credit quality classes using two applied models, CreditMetrics (developed by J. P. Morgan) and the KMV model (developed by Moody's KMV). Sensitivity analyses will be conducted to test for the robustness of results under different assumptions. The specific empirical results may be of direct interest to agricultural lenders, but the emphasis here is on developing models that can be used by agricultural lenders to comply with the New Basel Accord regulations.

Theoretical Models

The theoretical models are based on Merton's option pricing approach and credit value-at-risk methods. 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 expected loss given default are calculated using the values of assets and debt. Capital requirements for financial institutions are calculated using credit value-at-risk methods, which estimate probability distributions of credit losses conditional on portfolio composition (Sherrick, Barry, and Ellinger; Barry).

Merton's Model

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

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

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, that is, the value of assets is greater than the value of debt, debt can be refinanced 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

$$(2) \qquad \mathrm{PD}_{it} = \Pr[A_{it} \le D_{it}].$$

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

$$(3) \qquad \mathrm{PD}_{it} = \Pr\left[z_t \le -\frac{\ln[A_{i0}/D_{it}] + \left(\mu_i - \sigma_i^2/2\right)t}{\sigma_i\sqrt{t}}\right] \equiv \mathrm{N}(-\mathrm{DD}_{it})$$

where

$$(4) \qquad \mathrm{DD}_{it} \equiv \frac{\ln[A_{i0}/D_{it}] + \left(\mu_i - \sigma_i^2/2\right)t}{\sigma_i\sqrt{t}}$$

is called distance to default and $\mathrm{N}(\cdot)$ 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 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 difference 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 statistical 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

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

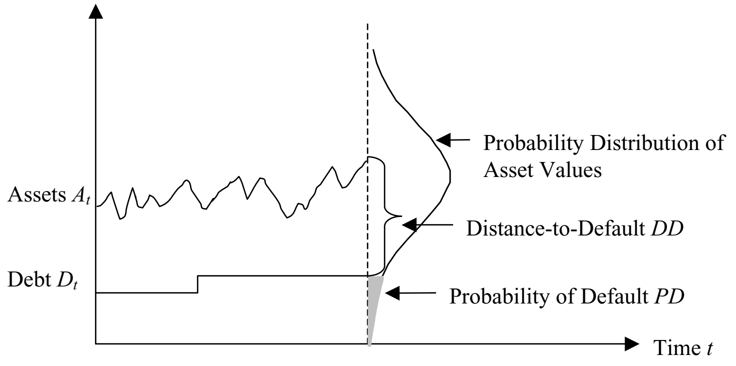


Figure 1. Probability distribution of asset values and distance-to-default

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 nondefaulting farms. This study calculates both the statistical probability of default and the historical default rate, measured in percentages.

Credit Risk and Capital Requirements Calculation

Two methods of considering credit risk are commonly used in determining portfolio values (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, some loan value may be lost depending on the quality of collateral pledged to secure the loan, the seniority of claims, possible loan guarantees, and administrative costs. In this study, loss given default is calculated as the percentage shortfall of assets below debt,

$$(5) \qquad \mathrm{LGD}_{it} = \frac{D_{it}^{\mathrm{d}} - (1-h)A_{it}^{\mathrm{d}}}{D_{it}^{\mathrm{d}}}$$

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 exposure at default EAD (defined as the value of farm debt),

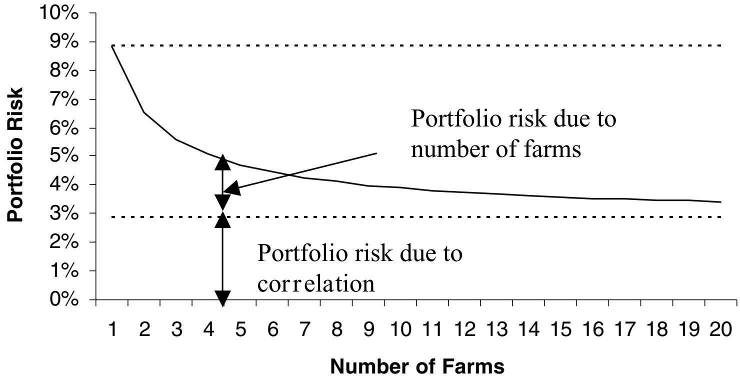
$$(6) \qquad \mathrm{EL} = (\mathrm{PD})(\mathrm{LGD})(\mathrm{EAD}).$$

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

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

The standard deviation of default for a portfolio of farms is

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



Note: 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 2. Effects of number of farms and correlation on portfolio risk

where w_i is the weight of farm i in the portfolio and ρ_{ij} is the correlation of default 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)
$$\begin{aligned} \mathrm{SD_p} &= \mathrm{SD}\sqrt{N(1/N)^2 + 2(N(N-1)/2)(1/N)^2\rho} \\ &= \mathrm{SD}\sqrt{\rho + (1-\rho)/N} \end{aligned}$$

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, that is, $\mathrm{SD_p} \rightarrow \mathrm{SD}\sqrt{\rho}$ 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, 2000 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(α), 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),

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

[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 classification where the mean default rate is 0.03%.

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(α), 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,

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

Credit value-at-risk 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,

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

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 or "market" farm, which in this study represents the fundamental factor, α_i and β_i are the coefficients to be estimated, and e_{it} is the idiosyncratic risk factor that is not correlated with the fundamental factor or with the idiosyncratic risk factors of other farms. Using statistics formulas, the variance of individual asset returns var(r_{it}), the covariance of asset returns cov(r_{it}, r_{jt}), and correlation of asset returns among farms ρ_{ij} can be represented as

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

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

and

$$(15) \quad \rho_{ij} = \frac{\sigma_{ij}}{\sigma_i \sigma_j} = \frac{\beta_i \beta_j \text{var}(r_{mt})}{\text{std}(r_{it}) \times \text{std}(r_{jt})}.$$

To summarize, a factor model is estimated by regressing the time-series of individual farm's asset returns on the average farm's asset returns. The coefficients are used in calculating the correlations between individual farms using equation (15). The average correlation is calculated as the average of the individual correlations and used in equation (9).

Two Applied Credit Risk Models

This article considers credit value-at-risk models of two vendors: CreditMetrics and Moody's KMV. Both models use Merton's asset value model and classify borrowers into credit quality classes. The advantage of credit quality classes is that the grouping of homogenous borrowers (called granularity) allows more precise estimation of probability of default and loss given default. The disadvantages of credit quality classes are that the precision of assigning borrowers into the appropriate credit quality classes decreases and that a large number of observations is needed to obtain reliable results for each credit quality class. 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.

The CreditMetrics Model

CreditMetrics extends Merton's model to include changes in credit quality. The CreditMetrics model is based on migration of borrowers from one credit quality to another credit

[4] For a portfolio with 1,000 borrowers ($N = 1{,}000$), 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 article, $K = 1$), the number of parameters to be estimated is $KN + K(K-1)/2 = 1{,}000$.

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 lenders usually use a credit scoring or risk rating approach to assign borrowers to credit quality classes (Splett et al.). Here, a risk rating approach is used to assign farmers into credit quality classes and to estimate a transition matrix reflecting the probabilities of migration between credit quality classes over time (Barry, Escalante, and Ellinger). The migration analysis used in this study assigns 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 (LGD) and expected and unexpected loss are calculated using equations (5), (6), and (10) for every credit quality class in the CreditMetrics model.

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 default occurs when the value of farm assets falls below the value of farm debt.[5]

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,

$$(16) \quad \mathrm{DD}_{it} = \frac{A_{it} - D_{it}}{\sigma_i^{\mathrm{A}}}$$

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), loss given default and the expected and unexpected loss are calculated for every credit quality class in the KMV model using equations (3), (5), (6), and (10).

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 an FCS institution would have borrowers with similar farm typology and characteristics.[6]

Farm-level data are obtained from the Illinois Farm Business Farm Management 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 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 eight years, which leads to 16,049 farm observations. All these observations are used in subsequent analyses except when a specific condition requires restricting the sample size.

Farms in default are defined as those with debt-to-asset ratios greater than one.[7] There

[5] 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 will be lower. This study follows the more conservative Merton definition of default.

[6] Agricultural lenders, however, must choose a subsample of farmers that closely matches the financial characteristics of their borrowers and use loss ratios for the subsample. Using average numbers from this study may lead to biased results because the farmers in this sample use different lenders.

[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.

Table 1. Descriptive Statistics

Debt-to-Asset Groups	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

[a]Farms with $D/A > 1$ are farms in default.
[b]The last row represents results for the average farm.

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).

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] 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 debt). Including both random changes in asset prices and changes in 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%.

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 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.

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).

[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.

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

Table 2. Expected and Unexpected Losses and Sensitivity Analyses

			Sensitivity Analyses			
Statistics	Using Historical Default Rate	Using Stat. Prob. of Default	Default if Debt > 0.9 *Assets	Actual Farm Weights	Correl = 0	Correl = 1
Prob. of default	0.785%	2.474%	1.642%	0.785%	0.785%	0.785%
Loss given default	35.458%	35.458%	18.761%	35.458%	35.458%	35.458%
Correlation	10.050%	10.050%	10.050%	10.580%	0.000%	100.00%
Farm std. of default	8.827%	15.534%	12.707%	8.827%	8.827%	8.827%
Portfolio std. of default	2.799%	4.926%	4.029%	2.871%	0.070%	8.827%
Expected loss[a]	0.278%	0.877%	0.308%	0.278%	0.278%	0.278%
	$846	$2,666	$936	$846	$846	$846
Unexp. loss 5%[b]	1.628%	2.865%	1.240%	1.670%	0.041%	5.133%
	$4,946	$8,704	$3,767	$5,073	$123	$15,598
Unexp. loss 1%	2.313%	4.070%	1.761%	2.372%	0.058%	7.293%
	$7,027	$12,366	$5,352	$7,208	$175	$22,160
Unexp. loss .5%	2.561%	4.506%	1.950%	2.627%	0.064%	8.075%
	$7,781	$13,693	$5,926	$7,981	$194	$24,538
VaR (95%)[c]	1.906%	3.742%	1.548%	1.948%	0.319%	5.412%
	$5,792	$11,370	$4,703	$5,920	$969	$16,444
VaR (99%)	2.591%	4.947%	2.069%	2.651%	0.336%	7.571%
	$7,873	$15,032	$6,288	$8,054	$1,021	$23,006
VaR (99.5%)	2.839%	5.384%	2.258%	2.905%	0.342%	8.354%
	$8,627	$16,359	$6,862	$8,828	$1,040	$25,384
No. farms in default	91	91	170	91	91	91
Farm obs.	16,049	16,049	16,049	16,049	16,049	16,049

[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.

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 eight 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 using the factor model, however, a survivorship bias was also introduced because farms that default and exit farming would not be included in the analysis.

In theory, asset return correlations can be calculated by taking correlations among all farms, however, 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 or "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

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

default rates, respectively (table 2). Using 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 32% 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 unexpected losses (and thus more economic capital is needed).

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.

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, that is, 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 2).[12] 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 2). These results are similar to the results in the base case using the historical default rates and demonstrate that 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 a uniform distribution leads 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 2). 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. This study shows that if farmer–borrower data are matched with external farmer data, correlations can be reasonably approximated by assuming a uniform distribution for these farms.

Correlation

Including correlations among farm performances in the analysis is an important strength of the methods used in this study. While the expected losses are the same as the base 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

[12] The rest of the analyses in this article use the historical default rate although the statistical probability of default can also be used.

Table 3. Credit Rating Migration Matrix (Used in the CreditMetrics Model)

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

Note. Classes are defined based on risk rating values. The migration matrix shows the probabilities of migrating from class i in year t to class j or default in year $(t + 1)$. The probabilities are measured in percentages.

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 2). 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, that is, 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 risk rating for the CreditMetrics model and their distance-to-default for the KMV model.

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. Five risk-rating classes were formed based on weighted measures of liquidity, solvency, profitability, repayment capacity, and financial efficiency (for more detail, see Splett et al.). A migration matrix was estimated showing the migration of farmers from one credit quality class to another credit quality or default next year (table 3). 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 0% probability of default, while farms starting in the worst credit class 5 will migrate into a default class with a 0.96% probability (table 3). These estimates of the probability of default were used in the calculations of expected and unexpected loss for each credit class. Table 4 shows the expected loss ranges from 0% of the portfolio debt for the best credit quality class (with rating 1) to 0.428% for the worst credit quality class (with rating 5). The unexpected loss, which will be exceeded with a 1% probability, 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 that reflect how far a farm is away from default or the number of 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.[13] The results show that farms that are at least 2 standard deviations away from default have a probability of default of 0.085%, whereas farms that are less than 0.1 standard deviations away from default have a probability of default of 7.72% (table 4). The expected loss ranges from 0.02% for the best credit quality class (with DD > 2) to 3.017% for the worst credit quality class (with DD $\leq$ 0.1). The unexpected loss, which

[13] 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.

Table 4. Expected Losses, Unexpected Losses, and VaR for the CreditMetrics and KMV Models

Classes	No. of Farm Obs.	No. of Default Farms	Prob. of Default (%)	Loss Given Default (%)	Expected Loss (%)[a]	Unexpected Loss (1%)[a,b]	VaR (99%)[c]
The CreditMetrics Model (classes based on credit risk ratings)							
Rating 1	2,732	0	0.000	–	0.000	0.000	0.000
Rating 2	2,349	1	0.030	50.700	0.015	0.655	0.671
Rating 3	2,444	9	0.421	15.689	0.066	0.752	0.818
Rating 4	1,429	9	0.888	15.497	0.138	1.077	1.215
Rating 5	880	10	0.960	44.565	0.428	3.226	3.654
The KMV Model (classes based on distance-to-default)							
$DD > 2$	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

[a]Losses are expressed as a percent of the total debt in the portfolio.
[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.

will be exceeded with a 1% probability, ranges from 0.516% for the best credit quality class to 7.736% for the worst credit quality class.

The CreditMetrics and KMV models emphasize granularity in their risk ratings and are widely used in the financial industry. The necessary capital requirements estimated using the two models differ because these models use different criteria to group borrowers into credit classes. Both models, however, estimate higher capital requirements for higher risk classes.

Summary and Conclusions

In this article, 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 credit risk models were based on Merton's option pricing approach and credit value-at-risk methods. These models were estimated for the portfolio of farms and then by grouping farms into different credit quality classes using CreditMetrics and the KMV models.

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 losses vary considerably among credit quality classes. An important goal of the New Basel Accord is to increase the granularity of the risk ratings and 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 here to address capital needs for operating, real estate loans, and other types of loans by calculating default rates and loss given default for each type.

The New Basel Accord and the modern approaches to credit risk modeling 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. The collection and storage of better data together with economic capital evaluation of loan portfolio risks will result in better estimation of the solvency of financial institutions.

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