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## RESEARCH

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## Preface

*Agricultural Finance Review* (*AFR*) provides a forum for discussion of research, extension, and teaching issues in agricultural finance. This publication contains articles contributed by scholars in the field and refereed by peers.

Volume 43 was the first to be published at Cornell University. The previous 42 volumes were published by the United States Department of Agriculture. *AFR* was begun in 1938 by Norman J. Wall and Fred L. Garlock, whose professional careers helped shape early agricultural finance research. Professional interest in agricultural finance has continued to grow over the years, involving more people and a greater diversity in research topics, methods of analysis, and degree of sophistication. We are pleased to be a part of that continuing development. We invite your suggestions for improvement.

*AFR* was originally an annual publication. Starting with volume 61, Spring and Fall issues are published. The *AFR* web page can be accessed at http://afr.aem.cornell.edu/. Abstracts of current issues and pdf files of back issues since 1995 are available.

The effectiveness of this publication depends on its support by agricultural finance professionals. We especially express thanks to those reviewers listed below. Grateful appreciation is also expressed to the W. I. Myers endowment for partial financial support. Thanks are also due to Faye Butts for receiving, acknowledging, and monitoring manuscripts, and Judith Harrison for technical editing.



Manuscripts will be accepted at any time.

# Application of Credit Risk Models to Agricultural Lending

*Lyubov Zech and Glenn Pederson*

## Abstract

A credit risk model suitable for agricultural lenders is identified. The model incorporates sector correlations and is applied to the loan portfolio of an agricultural credit association to create a distribution of loan losses. The distribution is used to derive the lender's expected and unexpected losses. Results of the analysis indicate that the association is more than adequately capitalized based on 1997–2002 data. Since the capital position of the association is lower than that of most other associations in the Farm Credit System, this raises the issue of overcapitalization in the System.

*Key words:* agriculture, capital adequacy, credit risk models, economic capital, portfolio risk analysis, value-at-risk



Applications of the modern portfolio management tools and concepts to agriculture are necessitated by the need for better capital and portfolio risk management in agricultural lending institutions. In mid-2004, the average permanent capital ratio for the Farm Credit System (FCS) associations stood at nearly 17.2%. More significantly, the permanent capital positions of System associations varied between 11% and 45%, all well above the 7% minimum capital requirement established for the FCS (Farm Credit Administration, 2004). While these high capital levels reflect the focus on safety, they do not appear to represent clearly established targets at the System or individual association levels (Barry, 2001), as the level of risk exposure has remained extremely low since 1995 (as measured by the percentage of loans in nonaccrual status or over 90 days past due).

New credit risk models allow portfolio managers to quantify risk at both the portfolio and individual loan contribution levels. These models can be used to estimate a lender's probability density function for credit losses and derive the amount of capital needed to cover those losses. Moreover, they incorporate correlation relationships between loan categories, which has been done historically on an intuitive basis. Consequently, these models facilitate a more informed approach to setting loan limits and reserves, and potentially a more consistent basis for economic capital allocation. The application of these models may help agricultural lenders and their regulators to identify more risk-efficient levels of economic capital.

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While portfolio models can make a significant contribution to better capital management decisions, agricultural lenders may be limited in their opportunity to simply apply the credit models that have been developed. These are data-intensive tools that were initially developed for use by commercial banks, and the data requirements may present a problem for FCS institutions. Banks can use comparable historical data collected by ratings agencies such as Moody's (Carty and Lieberman, 1998) or Standard & Poor's (Brand and Bahar, 1999). In contrast, agricultural lenders cannot rely on access to financial market data (stock prices, external credit ratings, historic default rates and volatility measures, or other market information published by rating agencies) to assess client risk. Rather, they must find ways to adapt the principles of these models to their loan portfolios and their information systems. In addition to data issues, agricultural lenders must ensure that the credit model assumptions and conceptual approaches are appropriate for modeling credit risk in agriculture.

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

The first objective includes examining the underlying assumptions and data needs of the existing credit risk models to determine if they are suitable for modeling credit risk in agriculture. The most appropriate methodology is modified to adapt it to agricultural lending. The second objective involves the application of the model to a representative Farm Credit System association. This objective includes appropriate parameterization of the model based on historical data that are consistent with the regulatory guidelines of the Basel II Capital Accord. The results show how an agricultural lender may adapt this model to evaluate capital adequacy and to conduct portfolio risk analysis.

## Characterizing Loan Losses

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

Economic capital is used to cushion unexpected losses due to the overall risks of conducting business—usually categorized into credit, market, and operational risks (Ong, 1999; Basel Committee on Banking Supervision, 2004). Credit risk, the focus of this paper, is the primary source of risk for a lender since it captures the risk of loss from borrower defaults. Credit risk incorporates borrower creditworthiness, transaction structure, and concentration risk. Market risk usually refers to possible losses in the market values of financial assets. This is generally confined to adverse changes in the market value of the trading portfolio during the period prior to liquidation of the assets or to taking a hedge position (Bessis, 1998). Operational risk results from internal processes, people, and systems, or from external events such as legal risk, computer failures, fraud, and poor monitoring. Most lending institutions compute total economic capital as the sum of the economic capital allocations for each type of risk.

This study focuses on estimating the distribution of loan losses due to credit risk. The loan loss distribution, illustrated in Figure 1, is a continuous-form representation, since it is characterized by a smooth distribution with a fat right tail. Small losses have a lower bound of zero

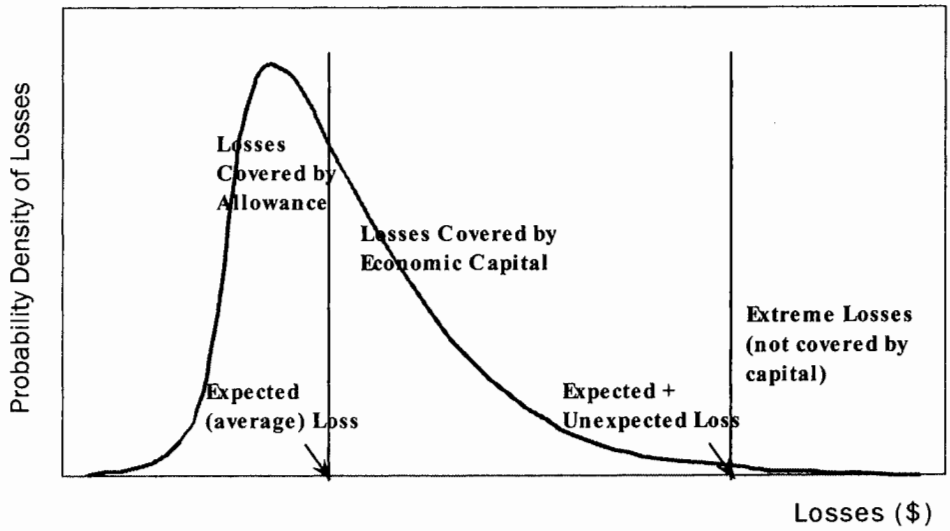


**Figure 1. Probability Density Function of Loan Losses**

but may occur with higher probability, while large losses typically occur with low probabilities. The expected loss is a long-run average measure that is accounted for in loan pricing and covered by the loan loss reserve (allowance for loan losses). The key characteristics (inputs) of expected loss (EL) are the probability of default (PD), loss given default (LGD), exposure at default (EAD), and time horizon (Ong, 1999; Basel Committee on Banking Supervision, 2004).

The expected loss of a loan can be calculated as the exposure at default adjusted for probability of default and loss given default, i.e., $EL = EAD * PD * LGD$. Here, the probability of default is the probability that a loss will occur over a given horizon, and the loss given default is the amount that is net of loan loss recovery in the case of default. Both PD and LGD are usually expressed in percentage terms, but the exposure at default is the unpaid amount of loan at the time of default. The resulting expected loss of a loan portfolio is equal to the sum of the expected losses of the individual loans.

Unexpected loss is the maximum potential loss at a given level of confidence (usually 99% to 99.99%). The unexpected loss is not accounted for in pricing, and it requires economic capital to cover the loss with the target level of confidence. Economic capital is the tail percentile that represents the total amount of risk (value-at-risk) less the expected loss covered by the loan loss reserve (see Figure 1). Extreme losses are associated with the area under the loss curve above the 99% to 99.99% level of confidence. Because events falling in this range occur so rarely, it is generally assumed that it is too costly to hold enough capital to fully cover them.

The probability density functions (PDFs) of loan losses for the whole portfolio vary among different portfolios, but they tend to be both highly skewed and leptokurtic (Ong, 1999). The shape of the portfolio PDF is dependent on the portfolio composition: loan default probabilities, relative loan sizes, correlations of default between loans, and concentrations by the number of loans and sector (or industry).

Unexpected losses of a portfolio are generally assumed to be much smaller than the sum of the individual unexpected losses because of diversification effects (low or negative correlation among unexpected defaults of different borrowers).

Only a portion of each loan's unexpected loss contributes to the portfolio's total unexpected loss. The incremental risk that a single loan contributes to the portfolio is called the risk contribution. It depends on the correlation of default of a given loan with other loans and represents undiversified risk of a loan in the portfolio (Ong, 1999).

## Basel II Capital Accord

The Basel Committee on Banking Supervision is proposing to introduce new risk-based requirements for internationally active banks and other significant banks by the end of 2007. These requirements will replace the relatively risk-invariant requirements in the current accord. The new Basel Accord will allow lenders to choose between the standardized approach and the internal ratings-based (IRB) approach, which can be either a "foundation" or "advanced" approach in the case of credit risk.

Under the standardized approach, the previous uniform 100% risk weight for private obligors has been replaced by four weightings: 20%, 50%, 100%, and 150%, depending on the obligor's risk rating. Under the foundation IRB approach, a bank develops its own PD for each borrower and relies on supervisory rules for the estimation of LGD and EAD, which are calibrated using fairly conservative assumptions and historical data in commercial lending. Under the advanced IRB approach, a bank develops its own estimates of PD, LGD, and EAD.

## Model Selection

In the financial world, the four most prominent credit risk models are Portfolio Manager (Moody's KMV Corporation, released in 1993), CreditMetrics (RiskMetrics Group of J. P. Morgan, released in 1997), CreditRisk+ (Credit Suisse Financial Products, released in 1997), and CreditPortfolioView (McKinsey and Company, 1997). Table 1 provides a brief comparison of these four models. Despite their different characteristics, recent studies conclude that these models are similar in their underlying structure and they produce almost identical results when they are parameterized consistently and the models are correctly specified (Koyluoglu and Hickman, 1998; Gordy, 2000; Finger, 1999).

Based on agricultural loan data availability and the ability to satisfy model assumptions, CreditRisk+ appears to be the most appropriate model for agriculture. In each of the other models the typically available agricultural lending data are insufficient, and a number of questionable assumptions need to be made in order to apply them.

For example, KMV Portfolio Manager generates empirical default probabilities by maintaining a large worldwide historical database of firm default data. Since the corporate default data are not comparable to defaults of agricultural producers, a strong assumption would need to be made that asset values are normally distributed around the current firm's asset value. Also, KMV uses a firm's stock price to estimate the market value of assets. Because most agricultural producers do not have stock and are not comparable to publicly traded companies, the market values of assets would have to be approximated by the adjusted book values of assets. In addition to making default probabilities less accurate, this method renders the correlations of loan defaults less meaningful as they are represented by the correlations in asset values. Moreover, this method also makes correlations of market values of assets (which represent correlations of loan defaults) less useful. Compared to other credit risk models, CreditRisk+ has the added advantages of requiring relatively few inputs and being relatively easy to implement and computationally attractive (Crouhy, Galai, and Mark, 2000).

**Table 1. Summary of the Four Major Credit Risk Models**

| | Credit Risk Model | | | |
|---|---|---|---|---|
| **Description** | **KMV Portfolio Manager** | **Credit Metrics** | **Credit PortfolioView** | **CreditRisk+** |
| Model approach | Option-based | Option-based | Econometric | Actuarial |
| Definition of risk[a] | MTM or DM | MTM | MTM or DM | DM |
| Risk drivers | Asset values | Asset values | Macro factors | Expected default rates |
| Data needs | Asset values, asset value volatilities | Credit spreads, yields for risk ratings, asset value volatilities | Economic factors driving default rates, borrower sensitivities to economic factors | Default rates, default rate volatilities |
| Correlation of credit events | Multivariate normal asset returns | Multivariate normal asset returns | Reflected by factor loadings | Correlation with expected default rate |

[a] The DM (default mode) paradigm assumes that the credit loss happens only when a borrower defaults within the planning horizon. The MTM (mark-to-market mode) paradigm assumes that the credit loss occurs when credit quality deteriorates.

The CreditRisk+ model[1] is based on an actuarial approach that uses mortality analysis to model a sudden event of borrower default. No assumptions are made about the cause of default, and the loan default event is represented by a Poisson distribution. Loan default probabilities are tied to the mean default probability of sectors (or industries), which vary according to a gamma distribution. Within each sector borrowers are presumed to respond to the same systematic risk factors. These factors may cause the incidences of default to be correlated, even though there is no causal link between them. Because the risk of default is assumed to fit a certain distribution, it is possible to calculate the distribution of portfolio losses analytically without the need to perform Monte-Carlo simulations (see CSFP, 1997, for more details).

Since the release of the original CreditRisk+ model in 1997, several studies have addressed its shortcomings. By modifying the mathematical components of the model, one can enhance the model to overcome its limitations, while remaining within the analytical approach of the original model. This study enhances the original CreditRisk+ model in two ways: first, by using an alternative algorithm that is more accurate, stable, and robust (Gordy, 2002); and second, by accounting for correlations between sectors (Bürgisser et al., 1999).

The model structure is illustrated in Figure 2. The model inputs are net loan loss exposures, default rates and their volatilities, and correlations of loan default between industries. The outputs include the expected and unexpected loan losses at the portfolio level that can be decomposed into loan risk contributions and risk contributions by sector such as industry or loan type. Thus, the model requires relatively minimal inputs, yet it generates the key portfolio, subportfolio, and loan-level results that are important for portfolio risk management.

## Model Parameterization

AgStar Financial Services, ACA is a member-owned cooperative that provides credit and credit-related services to eligible shareholders for qualified agricultural purposes. Following a recent merger with Farm Credit Services of Northwest Wisconsin, AgStar's assets are $2.3 billion, and its number of clients is approximately

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

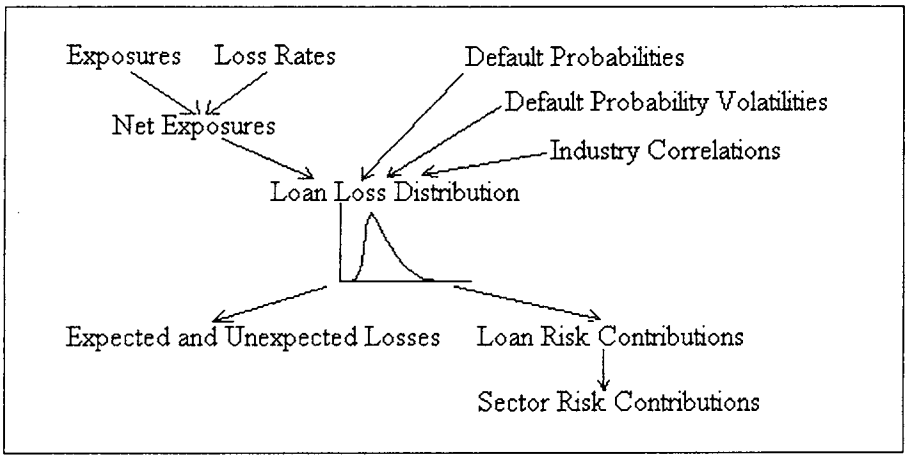


**Figure 2. The Model Structure**

15,000. AgStar operates in 69 counties in Minnesota and northwest Wisconsin. Capital is the equity or ownership of stockholders in the assets of the institution. Capital in associations is derived from two primary sources—investments by borrowers and retained earnings from operations. In 2002, AgStar's permanent capital ratio was just above 12% (AgStar Financial Services, 2003).

AgStar's annual year-end data for 1997 through 2002 is used for deriving the model parameters and to estimate the economic capital requirements in 2003. The data include various borrower, loan, and lease information. Loans and leases are collectively referred to as "loans" in this study. Most of the parameters required by the model are the parameters required for the internal ratings-based (IRB) approach. The Basel II recommendations for the IRB foundation approach for corporate exposures are used as guidance for the parameters where historical data are insufficient to provide precise parameter estimates.

## Definition of Default

Consistent with the Basel II definition of default, this study assumes a borrower is in default if she/he files for bankruptcy, foreclosure occurs, or if one or more of his/her loans or leases meet at least one of the following conditions: (*a*) became nonaccrual, (*b*) are delinquent 90 days or more, (*c*) have a charge-off, or (*d*) become subject to distressed restructuring. This definition of loss is used consistently in determining exposure at default, probability of default, and loss given default.

## Exposure at Default

Exposure at default (EAD) is defined as the expected exposure upon default of the borrower. Exposure at default is equal to the sum of loan volume and a percentage of the unfunded commitment that represents the probability of additional draw-down prior to default.[2] For the EAD we use data for December 31, 2002, and adjust the data for loans sold to other entities and loan participations.

## Default Probabilities and Their Volatilities

Since a client's risk-rating grade represents the probability of default, the associated default probabilities and their deviations are calculated for each risk

[2] This is taken to be 75% in the study according to the foundation approach of Basel II.

rating. Risk ratings[3] range from the highest quality grade to the loss grade. Acceptable risk ratings are from 1 to 4, a rating of 5 is special mention, ratings of 6 to 8 are unacceptable ratings, and 9 is a loss loan. Accordingly, the Basel II Capital Accord requires that all loans have a borrower risk rating assigned to them. However, AgStar currently does not require borrower risk ratings for clients with quite small loans. To ensure all loans have a risk rating, risk ratings are assigned to loans as follows:

- For the loans that have both customer risk rating and loan risk rating, the customer risk rating is used (for 77.6% of loan volume);
- For the loans without customer-level risk ratings, the worst loan risk rating is used to approximate the borrower's probability of default (for 13.3% of loan volume);
- For the loans without customer or loan risk ratings, the credit score is mapped into a risk rating using AgStar's guidelines (for 8.5% of loan volume); and
- For the loans without any kind of risk rating or credit score, a risk rating of 3 is used, which assumes that these loans are of acceptable quality (for 0.5% of loan volume).[4]

The IRB approach in the Basel II Capital Accord requires estimating a one-year probability of default for each of its internal rating grades. Estimates of PD must represent a conservative view of a long-run average PD. AgStar's data are sufficient to satisfy Basel's requirement of the minimum of five years of historical observations to estimate probability of default. The average annual historical PDs for each risk rating are reported in the second column of Table 2. In each case, the annual default probability for each borrower risk rating is calculated as the ratio of the number of customers whose loans defaulted over a given year to the number of nondefaulted customers with unpaid loans at the beginning of the year. Risk-rating scores for the beginning of the year are used, since default events can change the risk ratings during the year.

Using historical data series to calculate accurate estimates of the probabilities of default may be difficult, since annual frequency of observations does not allow for long time series. There may not be any defaults among high-quality obligors even in large samples, and a zero probability of default cannot be deduced from the fact that no defaults have been observed. One way to estimate the probability of default for the risk ratings of high-quality borrowers is to assume the probability of default is a function of the risk rating. Default probabilities increase exponentially with the increase in risk ratings. This is a clue that a logarithmic transformation of the default probability is needed to fit a linear regression.

After fitting an OLS regression model, $\mathrm{Ln}(PD) = \alpha + \beta * \textit{Risk Rating}$,[5] an exponential function is estimated and used to calculate the smoothed default probabilities: $\mathrm{Ln}(PD) = -7.211 + 0.827 * \textit{Risk Rating}$.

[3] AgStar assigns risk ratings to borrowers and to loans. Borrower-level risk rating is used to reflect the level of risk associated with a customer's ability to repay all outstanding loans. Risk ratings for loans are typically determined by the borrower's risk rating. When a borrower's risk rating changes, loan risk ratings update to the borrower risk rating, except when a loan risk rating is manually overridden. This may occur when a loan is protected by government guarantees or derivatives. Such loans have acceptable risk ratings even if the customer has a substandard risk rating. Thus, loan-level risk ratings may reflect both a borrower's probability of default and loss given default. FCS institutions re-rate loans when new information is obtained from a borrower. Mortgage loans may remain in the same risk rating for long periods if information is collected only at the time of origination.

[4] This is consistent with AgStar practices when nonrated loans are assigned to Acceptable-3 classification (Wilberding, 1999). As reported in Table 2, historical default probability for nonrated loans is very similar to default probability of loans with risk rating 3, validating this assumption.

[5] There are no outliers, influential observations, or problems with heteroskedasticity, and the regression has an $R^2$ of 0.98. Summary output is as follows:

| | Coefficient | Std. Error | *t*-Statistic |
|---|---|---|---|
| Intercept | -7.2106 | 0.2073 | -34.7888 |
| Coeff. on Risk Rating | 0.8272 | 0.0464 | 17.8482 |

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

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

The values of this log function are reported in Table 2 (column 4). Customers with risk ratings 8 and 9 are assigned a default probability of 100% because all customers in these risk ratings are in default.

## Default Rate Volatility

The historical standard deviations of default rates are presented in Table 2 (column 3). The standard deviations of default rates are modeled as a function of the risk ratings. Standard deviations increase exponentially with risk ratings, similar to default probabilities. An ordinary least squares (OLS) regression is used to estimate the volatility function: Ln(*Std. Dev. PD*) = -7.422 + 0.753 * *Risk Rating*.[6]

## Loan Risk Migration

The effect of loan risk migration is included in the estimates of default rates and their volatilities. In order to be consistent with AgStar's stress-testing practices of applying past migration trends to current portfolios, an assumption is made that average historical migration patterns will continue in the future. Average risk migrations are calculated based on annual AgStar data during 1997/98 through 2001/02 (see Table 3). Only the customers who are not in default both in the beginning and at the end of the year are included in the migrations.

Annual probabilities of default and their standard deviations are adjusted by migrations. Default probability adjusted for migration is the sum of smoothed default probabilities for the risk ratings (see Table 2) weighted by the percentages of clients in the risk ratings at the end of the period (Table 3).[7] Similarly, the standard deviation of default volatility adjusted for migration is the sum of smoothed standard deviations (see Table 2) for the risk ratings weighted by ending risk migration percentages

[6] There are no outliers, influential observations, or problems with heteroskedasticity, and the regression has an $R^2$ of 0.95. Summary output is as follows:

| | Coefficient | Std. Error | *t*-Statistic |
|---|---|---|---|
| Intercept | -7.4225 | 0.3294 | -22.5315 |
| Coeff. on Risk Rating | 0.7529 | 0.0737 | 10.2204 |

[7] For example, the adjusted default probability for risk rating 1 is 0.257% (= 0.169% * 89.39% + 0.386% * 6.05% + 0.884% * 3.03% + 2.021% * 1.22% + 4.621% * 0.18% + 10.567% * 0.05% + 24.167% * 0.07%).

**Table 3. Average Annual Migration of Borrower Risk Ratings, 1997–2002 (percent)**

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

**Table 4. Probabilities of Default and Their Standard Deviations Adjusted for Migrations (percent)**

| Risk Rating | PD Adjusted | Std. Dev. of PD Adjusted |
|---|---|---|
| 1 | 0.257 | 0.178 |
| 2 | 0.514 | 0.340 |
| 3 | 1.158 | 0.712 |
| 4 | 2.440 | 1.404 |
| 5 | 5.218 | 2.826 |
| 6 | 10.061 | 5.192 |
| 7 | 22.173 | 10.693 |
| 8 | 100.000 | 0.000 |
| 9 | 100.000 | 0.000 |

(Table 3).[8] See Table 4 for default probabilities and their standard deviations adjusted for risk migrations.

## Loss Given Default

Because of insufficient internal data to estimate loss given default, the LGD rates in this study are based on the preliminary information from the Farm Credit System President's Commission on Credit Risk. That Commission has adapted the Basel II Capital Accord to agricultural lending (Anderson, 2004). The Commission has identified four LGD grades (see Table 5).

[8] For example, the adjusted standard deviation of default probability for risk rating 2 is 0.340% (= 0.127% * 2.88% + 0.269% * 87.54% + 0.572% * 6.22% + 1.214% * 2.66% + 2.578% * 0.37% + 5.473% * 0.24% + 11.62% * 0.08%).

**Table 5. Loss Given Default Ratings and Loss Rates (percent)**

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

When AgStar assigns LGD ratings to all of its loans in the future, internally assigned LGD ratings should be used in the model to provide consistency between the parameters used for regulatory purposes and the model. In this study, the assignment of loans to LGD ratings is done in accordance with Farm Credit System proposed guidelines. The assignments are sufficiently conservative to reflect the risks of collateral volatility and exposure volatility.

LGD rating 1 is assigned to loans guaranteed by government agencies and to loans protected by credit derivatives. Loans with collateral-to-loan values over 150% are also included in this category. An LGD rating of 2 is assigned to loans with collateral-to-loan values between 100% and 150%. Leases are also included in this category since leased assets are returned to the lender in the event of default. An LGD rating of 3 is assigned to loans with collateral-to-loan values between 50% and 100%. Short-term and intermediate-term loans without collateral

**Table 6. Correlations of Default Probabilities Between Industry Categories**

| Industry Category | Crops | Dairy | Swine | Other Livestock | Landlord | General Farms | Rural Residence | Others |
|---|---|---|---|---|---|---|---|---|
| **Crops** | 1.00 | 0.67 | 0.70 | 0.96 | 0.39 | 0.04 | -0.80 | -0.38 |
| **Dairy** | 0.67 | 1.00 | 0.27 | 0.82 | -0.29 | -0.03 | -0.61 | -0.31 |
| **Swine** | 0.70 | 0.27 | 1.00 | 0.66 | 0.25 | -0.41 | -0.52 | -0.73 |
| **Other Livestock** | 0.96 | 0.82 | 0.66 | 1.00 | 0.13 | -0.12 | -0.86 | -0.51 |
| **Landlord** | 0.39 | -0.29 | 0.25 | 0.13 | 1.00 | 0.60 | -0.01 | 0.39 |
| **General Farms** | 0.04 | -0.03 | -0.41 | -0.12 | 0.60 | 1.00 | 0.39 | 0.90 |
| **Rural Residence** | -0.80 | -0.61 | -0.52 | -0.86 | -0.01 | 0.39 | 1.00 | 0.63 |
| **Others** | -0.38 | -0.31 | -0.73 | -0.51 | 0.39 | 0.90 | 0.63 | 1.00 |

*Note:* Time series of mean and annual default probabilities are calculated for each industry, and correlation coefficients are estimated for each pair of annual default probabilities.

information are also included in this category (unless they have an LGD rating of 1 or 2). AgStar's database contains collateral information on these types of loans only if they are adversely classified, even though many loans of these types have ample collateral. Placing these loans in an LGD rating of 3 is a reasonably conservative assumption. An LGD rating of 4 is assigned to unsecured loans and to loans with collateral-to-loan values below 50%. In assigning the LGD grades, the collateral-to-loan values include the unfunded commitment to the borrower.

## Sector Analysis

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

Based on the correlation structure, there appear to be two independent groups of industries. The first group represents the "traditional farm" economy. It includes crops, dairy, swine, and other livestock. Defaults in these industries are positively correlated. The second group represents the "general" economy. It includes rural residences, general farms, and others.

Default probabilities across these industries are also positively correlated. Default probabilities are negatively correlated between the traditional farm and general economy categories. Defaults in the landlord industry are somewhat correlated with both traditional farm industries and the general economy industries. The landlord industry is correlated with crops, general farms, and other industry. This is an expected result, since landlords usually receive most of their income from renting land to crop farmers and part-time farmers, so they are affected by both farm economy and general economy.

Because the model is not designed to handle negative correlations, industries where probabilities of default are negatively correlated are assumed to be independent (have zero correlation), resulting in a slight conservative bias of the resulting economic capital requirements.

**Table 7. Loan Loss Distribution Summary**

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

## Market and Operational Risks

The Farm Credit System has not developed rules on estimating capital for operational risk. Thus, the recommendations of the Basel II Capital Accord are used. The simplified, standardized approach for operational risk is the Basic Indicator Approach (applicable to any bank, regardless of its complexity or sophistication). Under this approach banks must hold capital equal to 15% of average annual gross income over the previous three years (Basel Committee on Banking Supervision, 2004, §649). Annual gross income based on AgStar's 2002 annual report is about $158.4 million, which makes operational risk capital equal to about 0.87% of the gross exposure.

Associations do not have trading book, foreign exchange risk, and commodity price risk exposures. Consequently, they are not required to hold market risk capital according to the Basel II regulations. Thus, there is minimal market risk capital required. Since the operational risk capital is estimated to be 0.87% of the gross exposure, the market risk capital is assumed to be 0.13% of the gross exposure. The resulting sum of operational risk capital and market risk capital is equal to 1% of the gross exposure, or just over $26 million.

**Table 8. Expected Loan Losses**

| Description | Amount | % Exposure |
|---|---|---|
| **Expected Losses on:** | | |
| Nondefaulted Loans | $12,781,624 | 0.49 |
| + Defaulted Loans | $10,398,970 | 0.40 |
| = Total Expected Losses | $23,180,594 | 0.89 |

# Model Results

The main output of the credit risk model is the loan loss distribution. Table 7 provides summary statistics for the analyzed portfolio and a summary of the resulting loan loss distribution. Total exposure is the sum of individual exposures including unfunded commitments weighted at 75%. Maximum loss is the sum of exposures multiplied by LGD rates. The distribution mean is the expected loss on nondefaulted loans. Tail percentiles show the value-at-risk, the total required risk funds to cover expected losses, and the unexpected losses.

## Capital Adequacy

The expected loss represents the required allowance for loan loss. In the Basel II Accord, it was agreed that the allowance could be recorded as capital against requirements. Thus, the difference between the value-at-risk at the selected percentile (such as 99.97%) and the mean is the required amount of credit risk capital. Since the establishment of the allowance impacts the level of capital, the adequacy of the allowance should be established first (Farm Credit Administration, 1994). Expected losses on defaulted loans are added to the expected losses on nondefaulted loans to arrive at the total expected losses shown in Table 8.

Charge-offs on defaulted loans should be counted against the expected losses as they are actual losses that have already been paid out of allowance. Subtracting charge-offs from the allowance requirements brings them down to almost $20 million. AgStar's book allowance is

**Table 9. Economic Capital at Various Confidence Levels**

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

$42.4 million—more than twice the required allowance under the chosen parameterization.

The loan loss distribution allows for the comparison of economic capital (at various confidence levels) to the existing risk funds (Table 9). Typical confidence levels range from 99.00% to 99.99%. The choice of the confidence level depends on the lender's level of risk aversion. The choice of the confidence level selected by a financial institution with risk-rated debt depends on the target debt rating. For example, a 99.90% capital level corresponds to a single-A debt rating. The Basel II Capital Accord uses the 99.90th percentile in deriving the regulatory function that targets a BBB rating. The 99.97th percentile (the equivalent of an AA rating) is used by many commercial banks, and it is used as a primary confidence level in this study. This confidence level means that AgStar would incur losses greater than economic capital in one out of 3,000 years under the given parameterization.

Table 9 (column 2) shows the value-at-risk (required total risk funds to cover losses at a given loss percentile). Credit risk capital is equal to the value-at-risk less the loan loss allowance. Economic capital needs to cover market and operational risks in addition to credit risk. The sum of credit risk capital plus market and operational risk capital is equal to total economic capital. Total economic capital (Table 9, column 7) can be compared with the lender's book capital. Economic capital as a percentage of risk-weighted assets (column 8) can be compared against the 7% permanent capital requirement. Risk-weighted assets are $2,222,644,152 as of December 31, 2002. Table 9 shows that the choice of confidence level is an important parameter. The amount of economic capital nearly doubles as the confidence level increases from 90.00% to 99.99%.

Table 10 provides a comparison of economic capital with the book capital of AgStar under the 99.97th loss percentile. Economic capital is $63,737,771, which is much less than the book capital of $269,829,000. Thus, under selected parameters, AgStar holds more than three times as much capital as the model economic capital requirement. Since AgStar appears to hold excessive economic capital, there is an opportunity to reduce its book capital. It is important to remember that the probabilities of default and their standard deviations were calculated based on the last five years, which were comparatively favorable for the agricultural economy due to government support programs. Ideally, these parameters should be averages over at least one economic cycle. Stress testing (to be covered later) is necessary to analyze the effects of economy deterioration on the

**Table 10. Comparison of Total Economic Capital (at the 99.97th percentile) with Book Capital as of December 31, 2002**

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

[a] Total Risk Funds are the sum of Total Economic Capital and Expected Loan Losses.
[b] Book Risk Funds are the sum of Book Capital and Book Allowance.

economic capital requirements. The Basel Capital Accord recommends that capital be sufficient in the event of at least a mild recession. The Farm Credit System would like to see associations capable of withstanding stress comparable to the stress of the 1980s.[9]

## Stress Testing

Stress testing gauges potential vulnerability of financial institutions to probable and exceptional (but plausible) events. Stress testing is widely used as a supplement for value-at-risk models. Stress testing is generally a way to measure and monitor the consequences of extreme movements in parameters. Value-at-risk is of limited use in measuring exposures to extreme market events because, by definition, such events happen too rarely to be captured by empirically driven statistical models (Committee on the Global Financial System, 2001).

Stress-testing scenarios show the effects of changes in several parameters reflecting events that can be historical or hypothetical, probable or extreme. Stress-testing scenarios are required by the Basel II Capital Accord. For the purpose of evaluating regulatory capital adequacy, the lender's stress test should consider not the "worst-case scenarios," but "at least the effect of mild recession scenarios" (Basel Committee on Banking Supervision, 2004, §435).

Table 11 shows model results under various historical and hypothetical economic scenarios. These scenarios were developed in consultation with AgStar's risk management team and in the absence of relevant empirical studies on agricultural lending. Loans that are in default are assumed to remain in default. Allowance, economic capital, and total risk funds margin are shown as dollar amounts and percentages of risk-weighted assets under the various scenarios. The risk funds margin (column 6) shows the excess of book risk funds (if positive) or the shortage of book risk funds (if negative). All of the scenarios are analyzed under the assumption of a 99.97th confidence level.

[9] This statement is based on information provided by AgriBank management staff.

**Table 11. Stress Testing at the 99.97th Percentile**

| [1] Scenario | [2] Allowance ($) | [3] % Risk-Weighted Assets | [4] Economic Capital ($) | [5] % Risk-Weighted Assets | [6] Risk Funds Margin ($) | [7] % Risk-Weighted Assets |
|---|---|---|---|---|---|---|
| Base | 23,180,594 | 1.04 | 63,737,771 | 2.87 | 225,312,635 | 10.14 |
| Mild Recession | 29,499,473 | 1.33 | 74,120,475 | 3.33 | 208,611,052 | 9.39 |
| Moderate Recession | 60,456,152 | 2.72 | 118,069,215 | 5.31 | 133,705,632 | 6.02 |
| Severe Recession | 92,102,402 | 4.14 | 189,342,480 | 8.52 | 30,786,118 | 1.39 |
| Crisis of 1980s | 129,274,260 | 5.82 | 472,610,785 | 21.26 | -289,654,045 | -13.03 |

The "Base" scenario repeats the results described earlier. The "Mild Recession" scenario assumes that 50% of the loan risk ratings and LGD ratings migrate to the next lower rating level. This scenario does not have much effect on the risk funds margin, decreasing it from 10% to 9% of risk-weighted assets. Under the "Moderate Recession" scenario, all risk ratings and LGD ratings are assumed to migrate downward by two risk ratings. Thus, all loans that are risk rated 1 become risk rated 3, all loans that are risk rated 2 become risk rated 4, and so on. Under this scenario, the risk funds margin decreases to 6% of risk-weighted assets. The "Severe Recession" scenario assumes default probabilities and their standard deviations triple, and the LGD rates double. The scenario increases the need for risk funds more than three times over that in the "Base" scenario. Book risk funds are still sufficient to withstand the increased risk in the portfolio at the 99.97% confidence level, and the risk funds margin remains over 1% of risk-weighted assets.

The "Crisis of 1980s" scenario assumes that default probability and its standard deviation[10] is 10% for loans in all risk-rating classes, reflecting the fact that in Minnesota, 24% of commercial farms faced default in 1984–86, and 10% were technically insolvent (Hanson, Parandvash, and Ryan, 1991). There were wide variations in the loss rates across the nation during the mid-1980s, but Minnesota was a state most severely affected by the crisis. The scenario assumes LGD rates increase by 50% for all LGD ratings (LGD for rating 4 is capped at 100%), taking into account a decline in land values by about 50% during 1981–87. The book risk funds show significant shortage under this scenario at the 99.97th percentile. However, the funds are still sufficient under the 95th percentile, meaning there is a shortage of funds in one out of 20 years. Considering that a crisis similar to the one of the 1980s lasts less than 20 years, AgStar would have sufficient capital to withstand a comparable event. Overall, the stress-testing analysis indicates AgStar is adequately capitalized to withstand a recession, even a severe one or a farm financial crisis.

## Portfolio Management

The credit risk model is a potentially powerful instrument for portfolio managers. The information generated by the model is useful to agricultural lenders since it quantifies portfolio risk. This makes it possible to monitor changes in credit risk, engage in risk-based pricing, and develop credit limit systems. Also, portfolio diversification can be measured from the loan loss distribution. A low level of loan diversification by industry is expected to result in a relatively wider spread of the distribution curve (a long and fat tail) and a higher level of required capital.

[10] No information is available on the standard deviation of default probability during the events of the 1980s. Thus, we adopt Wilde's (2000) recommendation to assume that the standard deviation of default probability is equal to 100% of the mean consistent with the previous default experience in the United States.

By allocating economic capital across all of the loans in a portfolio, this type of model can be used to identify the most risky exposures. By comparing economic capital requirements before and after the inclusion of loans in a portfolio, the model can be used to analyze the effect of the potential of portfolio adjustments. The effects on the portfolio quality and capital requirements can also be analyzed. Moreover, economic capital requirements for new loans can be assessed and used for risk-based loan pricing.

Economic capital requirements can be allocated across various portfolio segments, such as industry, loan type, or risk-rating classification to analyze concentration risk and set credit limits. Economic capital and expected losses can be used as inputs for risk-adjusted return on capital (RAROC) analysis for individual loans, portfolio segments, and the overall portfolio. RAROC gives the lender an ability to apply the same measure to consistently compare business lines with different risks, estimate tradeoffs between risks and returns, price loans on a risk-adjusted basis, and set hurdle rates that can be used to evaluate profitability of transactions across product lines. Thus, credit models may increase the transparency and understanding of risks for portfolio managers.

## Conclusions

A CreditRisk+ type model is deemed most suitable for agricultural lending since its data requirements can be satisfied by the available data, and its assumptions are most appropriate for modeling credit risk in agriculture. The disadvantages of the original CreditRisk+ model are overcome in this study by incorporating recent research (accounting for sector correlations and using a more stable and accurate algorithm).

This study parameterized the model using a representative agricultural credit association's historical data and showed how an agricultural lender can transition from a historically regulatory approach to capital needs to an economic capital approach. Application of the model shows that AgStar is more than adequately capitalized. Because AgStar's capital position is lower than that of most other associations, this raises the issue of overcapitalization within the Farm Credit System. By holding an optimal level of capital, lenders may increase their efficiency, provide for safety and soundness, potential asset growth, and long-run institutional viability. Thus, application of well-calibrated credit risk models can potentially result in lower aggregate capital requirements, but requirements that recognize the level of risk exposure present in the loan portfolio. In turn, lower levels of capital may benefit FCS borrowers in the form of reduced loan rates and improved access to loanable funds.

Credit risk models are useful for extending the practice of portfolio-level risk analysis, since they generate information that may improve the overall ability of portfolio managers to identify, measure, and control credit risk. This is already being done by large commercial banks, and it is just a matter of time until it becomes more commonplace in agricultural lending institutions. An agricultural lender may use this type of model to manage and monitor portfolio risk, analyze the effects of changes in portfolio composition and diversification, set risk-based concentration limits, evaluate risk-adjusted profitability, and perform risk-based loan pricing.

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# Bank Risk Ratings and the Pricing of Agricultural Loans

*Nick Walraven and Peter J. Barry*

## Abstract

This paper reviews the prevalence of the use of risk ratings by commercial banks that participated in the Federal Reserve's Survey of Terms of Bank Lending to Farmers between 1997 and 2002. Adoption of risk rating procedures held about steady over the period, with a little less than half the banks on the panel either not using a risk rating system, or reporting the same rating for all their loans in the survey. However, most of these banks were small, and roughly four-fifths of all sample loans carried an informative risk rating. After controlling for the size and performance of the bank and as many nonprice terms of the loan as possible, findings reveal that banks consistently charged higher rates of interest for the farm loans they characterized as riskier, with an average difference in rates between the most risky and least risky loans of about 1½ percentage points.

*Key words:* agricultural finance, agricultural loans, interest rates, risk ratings

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The management of risk by commercial banks in the United States and other developed countries has advanced significantly to now address the frequency and severity of loss and an enterprise-wide perspective on credit, market, and operational risks. The goals of risk management are to refine the measures of risk, better match economic capital to the overall risk profile, allocate capital efficiently among the respective bank enterprises, and to price loans and other products and services consistent with their marginal contributions to economic capital and risk-adjusted returns on capital (Matten, 2000; Beisses, 2002; Smithson, 2003; Saunders and Allen, 1999).

International banking regulators are utilizing this greater precision in assessing lending risks by publishing risk-sensitive capital requirements (commonly referred to as "Basel Accords"), first in 1988 and again in 2004. The ultimate goal of this regulatory process is to develop risk-sensitive capital requirements that are uniform across countries and to integrate risk management and bank supervision. The New Basel Accord emphasizes the refinements in risk management, while offering a menu of choices for credit risk measurement by institutions of different size, operating environments, complexities, and market characteristics. The menu ranges from an expanded set of risk weights compared with those in the 1988 Accord to internal-ratings-based approaches in which institutions estimate probabilities of default and loss-given-default, by rating classes of borrowers and loans.

The use of risk rating systems to summarize multiple features of a bank's customers or loans has been spreading

through the banking system for at least a decade, first among larger banks, and gradually to medium and smaller banks (Brady, English, and Nelson, 1998; Treacy and Carey, 1998). According to Brady, English, and Nelson, virtually all large banks rated loans in the August 1998 Survey of Terms of Bank Lending by the Federal Reserve System; in contrast, most medium to small banks either did not rate loans or assigned all the loans in the survey to a single rating category. Assessing the adoption of these risk, capital, and pricing practices by banks with different attributes is important to an understanding of the scope and depth of their management resources, their likely adoption of more sophisticated technology in the future, and the design of risk-based capital regulations for safety and soundness in a diverse banking system.

Little contemporary evidence is available regarding the use of such practices on agricultural loans.[1] In 2003, about half of lending to U.S. farmers by commercial banks occurred through smaller community banks that had less than $500 million of assets [U.S. Department of Agriculture/Economic Research Service (USDA/ERS)]; the rest came from larger, regional or national banks. The diversity in size and management of banks that lend to farmers suggests the need for a range of capital management and risk assessment guidelines and continued monitoring of structural change in agricultural lending.

This paper reviews the use of risk ratings, risk-adjusted pricing, and other responses to credit risk by commercial banks when making new agricultural loans. Quarterly data from the Federal Reserve's Survey of the Terms of Bank Lending to Farmers (STBLF) from August 1997 through August 2002 are utilized following the methods employed for business lending as reported by English and Nelson (1998). Bank characteristics, loan pricing, and other risk management tools are summarized, compared to the August 1998 findings of English and Nelson, and then evaluated using multiple regression procedures. The regression results show much stronger relationships among risk, pricing, and other risk control variables than do the descriptive comparisons alone.

## Surveying Banks About Agricultural Lending

The data for our analysis of risk pricing on agricultural loans come from the Federal Reserve's Survey of the Terms of Bank Lending to Farmers and from commercial bank call reports.[2] This section provides a brief history of the survey and reviews its current scope and the selection of its panel. (A more detailed description of the evolution of the survey can be found in Walraven and Slowinski, 1993).

In 1977, the Federal Reserve Board requested a quarterly survey of banks to gauge the cost, volume, terms, and purpose of credit extended to commercial businesses and to farmers. A single longitudinal survey of banks was developed to gather information about both types of lending. The survey has been modified since that time, most notably in 1989, when a separate group of banks was selected to report information on farm loans (some banks remained in both the business loan group and the farm loan group), and in 1998 when questions about the riskiness of loans were added to both surveys.

Since the survey's redesign in 1989, a stratified, random sample of 250 insured commercial banks reports information on

[1] For past studies of credit risk management by agricultural banks, interested readers are referred to Barry and Calvert (1983); Moss, Barry, and Ellinger (1997); Miller et al. (1993); and Swackhamer and Doll (1969). Also see Goodwin and Mishra (2000) for an analysis of risk premiums on farm loans using farmers' responses to the Agricultural and Risk Management Survey.

[2] The call reports are quarterly statements of financial information that are submitted to banking regulators. The information reported typically could be found on a bank's balance sheet or income statement.

each agricultural loan completed during the first week of the second month of each quarter.[3] Because the volume of agricultural loans is highly skewed across the universe of commercial banks, the first stratum of the survey includes 10 agricultural lenders that are among the largest holders of agricultural loans. The remaining commercial banks holding at least $1 million in agricultural loans are divided into four strata, with the members of each stratum holding successively smaller amounts of farm loans. Sixty banks are chosen randomly from each of these strata.

During the sampling week in each quarter, banks report the amount, the rate of interest, the maturity, and the nonprice terms of each new loan. In recent years, approximately 200 sample banks report roughly 4,000 loans in each survey.

## The Prevalence of Risk Rating in the STBLF Panel

About one-quarter of the banks in the panel (48 of 186) for the August 1998 STBLF did not rate farm loans, and almost as many (36 of 186 banks) assigned the same risk rating to all of the reported survey loans. Similar to the findings reported by English and Nelson (1998), almost all of the banks in the 1998 survey that either did not assign risk ratings or gave all loans the same risk rating were small banks (less than $1 billion in assets). As a group, these banks accounted for about 18% (739 of 4,072) of the total number of farm loans in the August 1998 survey.

Although anecdotal reports suggest the use of risk rating systems has been spreading for all types of loans, according to the STBLF responses, the proportion of banks that assigned risk ratings changed little during the five years following the 1998 English and Nelson business loan survey. In the August 2002 survey, about 20% of the responding banks (38 of 172 banks) did not rate farm loans, and about 25% (42 of 172 banks) reported no variation in risk ratings. In total, these 80 banks closed fewer than 9% of the loans reported in the August 2002 survey (440 of 5,105 survey loans), a proportion well below the 1998 reading, which suggests the proportion of farm loans having a risk rating has been growing.

Most of the banks remain on the survey from one quarter to the next; indeed, 120 of the banks that reported closing at least one loan in the August 1998 survey also reported a loan in August 2002. Among these banks, about 50 assigned loans to multiple risk categories in both 1998 and 2002. This set of banks reported about two-thirds of the number of sample loans (3,231 of 5,105) in the most recent survey. Another 10 banks that reported in both periods did not rate farm loans in 1998, but had begun to report ratings by 2002. A set of 22 banks that did not rate farm loans in 1998 still did not rate farm loans in 2002, and another 10 banks had discontinued rating farm loans by 2002. These 32 banks reported 245 loans in the August 2002 survey. The remaining 29 banks reporting loans in both 1998 and 2002 assigned the same risk rating to all the loans.

Although this singularity is unfortunate from an econometric point of view, to some degree it was inevitable. Most banks in the last group reported closing fewer than five loans during the August 2002 sample week. Because the risk descriptions were designed so that most loans fell in the middle of the risk scale, it seems plausible that a handful of loans at a particular bank all could be ranked similarly during the survey week.

[3] "Agricultural loan" refers to either of the farm loan definitions employed in the quarterly Report of Condition (call report). Included are both "loans to finance agricultural production or other loans to farmers" and "loans secured by farm real estate." Some of these loans are for nonagricultural purposes, although past surveys on purposes of farm real estate loans indicated that the incidence of nonagricultural use is low (Moss, Barry, and Ellinger, 1997; Barry and Calvert, 1983).

## Description of Risk Rating Categories

Banks participating in the survey are asked to map their internal risk ratings into a set of five rating categories which are described in detail in the reporting instructions. The loans are characterized in terms of the probability of a loss to the bank, rather than the probability of a default by the borrower.[4] As a result, requirements for compensating balances or collateral can reduce the risk rating of an otherwise more risky loan. Loans placed in category 1, the "minimal" risk category, should bear virtually no chance of loss to the bank. Loans in category 2 are described as "very unlikely" to result in a loss to the bank. Category 3 loans, termed "moderate risk," were intended to be an average loan to a typical borrower under average economic conditions. The survey was designed so that most loans would fall in category 3. Loans placed in category 4, although still bearing an "acceptable" degree of risk, were in some sense substandard. Category 5 loans were described as "special mention" loans, such as work-out loans—new loans typically would not fall in this category. Two additional rating categories were provided, the first for banks that rated but did not report some loans, and the other for banks that did not rate loans.

## Farm Loan Characteristics by Risk Rating

### The August 1998 Survey

In order to compare the 1998 English and Nelson averages for business loans to the STBLF data, we computed averages by bank size and risk category that were weighted by loan size and by a stratum expansion factor reflecting the ratio of the volume of farm loans outstanding at the panel bank to the volume outstanding at banks not in the survey. As shown in Table 1, panel banks in 1998 tended to adjust loan rates for credit risk in the sense that loans rated the least risky generally had lower rates and those rated most risky tended to carry higher rates. However, this relationship varied widely. Large banks (those having more than $1 billion in assets) closed transactions on loans with a risk rating of 3 which, on average, carried lower rates of interest than those with less risky ratings. For medium-sized banks (assets between $1 billion and $100 million) and small banks (assets less than $100 million), loans in category 4 tended to carry lower rates than loans in category 3. English and Nelson found closer correspondence between reported riskiness of commercial and industrial (C&I) loans and the average interest rate than these averages suggest for farm loans.

To the extent that reported rates of interest fail to increase with the reported risk rating, other characteristics of the loan likely compensate the lender for bearing the risk. To examine this possibility for the August 1998 survey, other reported features of the loans can be categorized by risk rating (Table 2). On average, farm loans in the survey were small; the overall weighted average amount for each loan was $27.3 thousand, with the weighted-average amount increasing uniformly with loan size from $15.6 thousand for the least risky loans to $79.3 thousand for the most risky loans.

In general, loans rated as less risky were more likely to be secured, consistent with the Berger and Udell (1990) hypothesis that collateral requirements often offset some of the credit risk. Furthermore, less risky loans tended to carry provisions allowing the bank to call the note before maturity, likely affording the bank some protection from post-closing changes in market interest rates. In addition, riskier loans were more likely to have been made under a prior commitment, which is

[4] The ratings thus reflect a single-dimension approach in which factors affecting frequency and severity of default are jointly considered. A dual rating approach separates the customer factors that influence the probability of default from the loan-related factors that determine severities of default.

**Table 1. Average Loan Rate by Risk Rating Class, August 1998 Survey of Terms of Bank Lending to Farmers (weighted by loan volume)**

| | Risk Rating Class (1 = least risky; 5 = most risky) | | | | | |
|---|---|---|---|---|---|---|
| **Bank Description** | **1** | **2** | **3** | **4** | **5** | **All** |
| Large bank | 7.98% | 8.83% | 7.96% | 8.77% | 9.10% | 8.44% |
| Medium bank | 9.39% | 9.68% | 10.22% | 9.92% | 10.16% | 10.00% |
| Small bank | 9.33% | 9.42% | 10.14% | 9.86% | 10.95% | 9.62% |
| All banks | 9.32% | 9.45% | 8.68% | 8.93% | 9.49% | 9.06% |

**Table 2. Loan Characteristics by Risk Rating Class, August 1998 Survey of Terms of Bank Lending to Farmers (weighted by loan volume)**

| | Risk Rating Class (1 = least risky; 5 = most risky) | | | | | |
|---|---|---|---|---|---|---|
| **Loan Characteristics** | **1** | **2** | **3** | **4** | **5** | **All** |
| Amount ($000s) | 15.6 | 16.7 | 31.2 | 53.7 | 79.3 | 27.3 |
| Percent w/collateral | 94.9 | 94.8 | 61.0 | 36.9 | 48.0 | 66.8 |
| Percent under commitment | 57.0 | 70.0 | 85.1 | 92.1 | 94.7 | 80.0 |
| Percent callable | 18.4 | 24.3 | 14.5 | 5.9 | 9.8 | 14.0 |
| Percent w/prepayment penalty | 0.1 | 0.1 | 3.5 | 0.8 | 0.5 | 1.6 |
| Average maturity (months) | 21.3 | 18.6 | 12.4 | 5.8 | 9.4 | 12.8 |

consistent with Morgan's (1998) hypothesis that, as economic conditions worsen, lenders make relatively more loans under preexisting commitments and relatively fewer new loans. Prepayment penalties, although rare overall, were more prevalent for loans in risk class 3 or above. Finally, the average maturity of the loans declined with reported riskiness, suggesting concerns about interest rate risk or repayment capability which were not sufficiently assuaged by call provisions, collateral requirements, and other terms of the loan.

### The August 2002 Survey

Despite a multitude of changes between 1998 and 2002 among agricultural lenders, the agricultural sector, and the general economy, we examined the August 2002 survey data within the same framework as the August 1998 survey. Summary statistics are reported in Table 3. In August of 2002, rates of interest at all sizes of banks showed a more consistent tendency to increase with credit risk, perhaps reflecting a better use of nonprice terms to adjust credit risk than in 1998. For instance, the proportion of loans that were secured rose to more than 90% in the August 2002 survey, well above the 67% figure four years earlier. In addition, loans in the riskier categories were much more likely to be secured in 2002. The proportion of survey loans the bank can call prior to the maturity date rose substantially for loans of average or lower risk (risk ratings 1 to 3).

## Controlling for Variations in Terms

In this section, regression analysis is used to examine the effects of various lending terms and bank characteristics on the rate of interest charged by the bank. The goal is to determine the strength of the relationship between loan pricing and risk while accounting for the effects of other controls on lending risk and the effects of

**Table 3. Summary Statistics for August 2002 Survey of Terms of Bank Lending to Farmers (weighted by loan volume)**

| | Risk Rating Class (1 = least risky; 5 = most risky) | | | | | |
|---|---|---|---|---|---|---|
| **Description** | **1** | **2** | **3** | **4** | **5** | **All** |
| **Rates by Bank Size:** | | | | | | |
| Large bank | 4.30% | 4.40% | 4.72% | 5.11% | 6.09% | 4.99% |
| Medium bank | 5.91% | 6.89% | 7.19% | 7.48% | 7.63% | 7.11% |
| Small bank | 7.04% | 7.01% | 7.78% | 8.19% | 9.46% | 7.36% |
| All banks | 6.75% | 6.86% | 6.00% | 5.39% | 6.54% | 6.05% |
| **Loan Characteristics:** | | | | | | |
| Amount ($000s) | 15.5 | 19.0 | 24.0 | 37.6 | 34.0 | 24.9 |
| Percent w/collateral | 95.0 | 96.2 | 88.6 | 95.1 | 98.8 | 92.7 |
| Percent under commitment | 76.4 | 73.3 | 74.7 | 93.1 | 92.2 | 80.3 |
| Percent callable | 27.0 | 28.2 | 30.3 | 3.9 | 3.3 | 20.6 |
| Percent w/prepayment penalty | 1.8 | 0.4 | 1.1 | 3.5 | 0.5 | 1.8 |
| Average maturity (months) | 21.5 | 11.8 | 15.9 | 10.0 | 5.5 | 13.2 |

the banks' characteristics. Data are included from all the quarterly surveys from August 1998 through May 2002, which provided 84,265 loans. Roughly following English and Nelson (1998), we include either quantitative or qualitative measures of all the nonprice terms of the loan as explanatory variables.

The STBLF incorporates some nonprice indicators that are not included in the STBL (nonfarm) survey. First, STBLF respondents indicate whether the loan is secured by farm real estate, some other type of security, or is unsecured. In contrast, STBL respondents indicate only whether the loan is secured. Over the entire sample, about 8.5% of the loans made were secured by farm real estate, although many of these loans have a relatively short maturity. The farm survey also asks whether the loan is insured by a federal agency, such as the Farm Services Agency (formerly the Farmers Home Administration). Finally, the farm survey asks whether the loan was made in participation with other banks, a traditional means used by rural banks to limit exposure to individual loans.

The regression specification also differs from English and Nelson by including bank-specific factors that might influence the loan rate of interest offered on the loan. Banks with a substantial portfolio of agricultural loans differ markedly across various size and performance measures. For example, in the March 2003 call report, almost half of farm loans were held by "nonagricultural" banks.[5] These institutions typically can diversify risks of farm lending against the overall portfolio, perhaps reducing the compensation they require for more risky loans. The ratio of the volume of the bank's farm loans to its total loans is thus included as a righthand-side variable.

In addition, the March call report indicates almost 60% of agricultural loan volume was held by banks with assets of less than $500 million. These small banks depend more heavily than larger banks on depository sources of loanable funds, and their cost of funding loans could differ substantially from larger competitors.

[5] In this paper, a nonagricultural bank is one that holds a proportion of agricultural loans in its loan portfolio which is smaller than the unweighted average of the ratios of agricultural loans to total loans at all commercial banks. In recent years, this average has held around 15% of total loans.

**Table 4. Summary of Regression Variables**

| Variable | | Mean | Std. Dev. |
|---|---|---|---|
| Risk Rating 1 (least risk) | (1 = yes, otherwise 0) | 0.054 | 0.227 |
| Risk Rating 2 | (1 = yes, otherwise 0) | 0.135 | 0.341 |
| Risk Rating 3 (average risk) | (1 = yes, otherwise 0) | 0.417 | 0.493 |
| Risk Rating 4 | (1 = yes, otherwise 0) | 0.224 | 0.417 |
| Risk Rating 5 (most risk) | (1 = yes, otherwise 0) | 0.059 | 0.235 |
| Risk Rating 7 (bank does not rate farm loans) | (1 = yes, otherwise 0) | 0.080 | 0.271 |
| Nonprice: Days until loan may be repriced | | 92.6 | 327 |
| Nonprice: Days until loan matures (0 if no stated maturity) | | 307 | 515 |
| Nonprice: Call provision (1 = yes) | | 0.190 | 0.392 |
| Nonprice: Prepayment penalty (1 = yes) | | 0.020 | 0.141 |
| Nonprice: Loan made under commitment (1 = yes) | | 0.854 | 0.353 |
| Nonprice: Loan secured (1 = yes) | | 0.907 | 0.290 |
| Nonprice: Loan secured by farm real estate (1 = yes) | | 0.085 | 0.278 |
| Nonprice: Loan made in partnership with another bank (1 = yes) | | 0.019 | 0.136 |
| Nonprice: Loan insured by federal agency (1 = yes) | | 0.040 | 0.195 |
| Nonprice: Natural logarithm of loan amount, Ln(*Loan Amount*) | | 2.44 | 1.55 |
| Bank: Natural logarithm of bank assets, Ln(*Bank Assets*) | | 14.80 | 3.18 |
| Bank: Return on Assets (ROA, percent) | | 1.40 | 0.730 |
| Bank: Farm Loans/Total Loans (percent) | | 23.40 | 24.70 |
| Bank: Interest Expense/Assets (percent) | | 2.99 | 0.784 |
| Bank: All Loans/All Deposits (percent) | | 85.40 | 21.80 |
| Bank: All Delinquencies/Total Loans (percent) | | 5.77 | 6.67 |
| Bank: All Net Charge-offs/Total Loans (percent) | | 0.35 | 0.45 |

Smaller banks are also less diversified geographically, making them more vulnerable than larger banks to adverse local events. For example, drought conditions in a couple of counties could cause repayment problems for many of a small bank's loan customers. To account for these potential differences, we add the natural logarithm of the bank's assets as an explanatory variable.

Several other ratios are related to bank performance: (*a*) return on assets, (*b*) interest expense/total assets, (*c*) delinquent loans/total loans, and (*d*) net charge-offs/total loans. Also included is the ratio of loans to deposits, a traditional indicator of bank liquidity.

Table 4 lists the variables used in the regressions, along with their respective means and standard deviations. Contrary to the previous tables, these statistics are calculated from raw, unweighted data. For instance, the mean of the 0-1 indicators shows that 5.4% of the sample loans fell in the least risky category, while 41.7% were rated in the third (typical risk) category. The average interval of loan repricing was about three months, while the average maturity was less than one year. Roughly 20% of the loans could be called by the bank, and few (about 2%) carried a prepayment penalty. More than 85% of the loans were made under a prior commitment, and more than 90% were secured (although relatively few were secured by farm real estate). The loans tended to come from more profitable banks—i.e., the average ROA for banks making the loans was 1.4%, considerably above the 1.1% average ROA for all small agricultural banks between 1997 and 2002 (Federal Reserve Board, *Agricultural*

**Table 5. Summary of Regression Estimates (dependent variable = *Effective Rate of Interest*)**

| Variable | Parameter | *t*-Value |
|---|---|---|
| Intercept | 7.55 | 88.54*** |
| **Loan-Level Variables:** | | |
| Risk Rating 1 (least risk) | 0.03 | 0.75 |
| Risk Rating 2 | 0.22 | 6.68*** |
| Risk Rating 3 (average risk) | 0.72 | 23.69*** |
| Risk Rating 4 | 0.70 | 22.35*** |
| Risk Rating 5 (most risk) | 1.34 | 37.08*** |
| Risk Rating 7 (bank does not rate farm loans) | 0.78 | 22.15*** |
| Days until loan may be repriced | -0.00025 | -12.62*** |
| Days until loan matures | 0.00004 | 3.13*** |
| Call provision | 0.25 | 17.10*** |
| Prepayment penalty | -0.33 | -9.00*** |
| Loan made under commitment | -0.30 | -18.44*** |
| Loan secured | 0.13 | 7.02*** |
| Loan secured by farm real estate | -0.44 | -22.63*** |
| Loan made in partnership with another bank | -0.50 | -13.32*** |
| Loan insured by federal agency | -0.17 | -6.22*** |
| Ln(*Loan Amount*) | -0.11 | -31.04*** |
| **Bank-Level Variables:** | | |
| Ln(*Bank Assets*) | 0.004 | 1.01 |
| Return on Assets (ROA, percent) | -0.21 | -27.11*** |
| Farm Loans/Total Loans (percent) | -0.007 | -18.48*** |
| Interest Expense/Assets (percent) | 1.05 | 111.14*** |
| All Loans/All Deposits (percent) | -0.02 | -49.34*** |
| All Delinquencies/Total Loans (percent) | -0.02 | -24.13*** |
| All Net Charge-offs/Total Loans (percent) | -0.38 | -29.95*** |
| No. of Observations = 84,265; Adjusted $R^2$ = 0.306; *F*-Statistic = 1,616 | | |

*Note:* Triple asterisks (***) denote statistical significance at the 1% level.

*Finance Databook*). The delinquency rate at banks making the loans was 5.77%, considerably greater than the typical delinquency rate at most agricultural banks.

The regression results for the entire sample are shown in Table 5. The adjusted $R^2$ is 31%, indicating that a substantial proportion of the variability in rates of interest reflects differences in the terms of the loans and in bank performance. The *t*-statistics for most variables were significant at the 1% level, and the *F*-statistic of 1,616 was highly significant.

After controlling for both the nonprice terms of the loan and the bank-specific differences, the coefficients for the risk rating indicators suggest a plausible and consistent pricing of loans according to their reported riskiness. For instance, a loan with the least risky rating, other factors equal, carried a 1.3 percentage point lower interest rate than a loan rated the most risky (coefficient on Risk Rating 1 minus coefficient on Risk Rating 5).

Coefficients on most other loan-level variables have plausible magnitudes. Loans with a prepayment penalty, issued under a prior commitment, issued in

partnership with another bank, or with federal insurance were priced lower than other loans, consistent with their risk-reducing properties. The coefficients on these nonprice terms indicated a reduction of 17 to 50 basis points for each characteristic, and all were highly significant.

Secured loans tended to carry significantly higher rates of interest, which is consistent with Berger and Udell's (1990) finding that banks tend to extend unsecured loans to their least risky customers. The loans secured by farm real estate carried substantially lower rates of interest. The reduction in rates associated with real estate collateral was highly significant, which reflects the value of farm real estate collateral as insurance against losses on loans.

Among bank-level variables, higher returns on assets were associated with lower rates on farm loans—i.e., more profitable banks tended to offer lower rates to their farm borrowers. In addition, banks that specialized in farm lending (as indicated by their farm loan ratios) tended to offer lower rates on their farm loans. While the parameter associated with the farm loan ratio was highly significant and suggests some efficiencies in making farm loans, the effect was relatively small. In contrast, the parameter on the ratio of interest expense to bank assets, a proxy for the bank's cost of funds, was large and highly significant. Indeed, the coefficient of about unity suggests that banks tended to pass higher funding costs directly to their borrowers. In addition, greater bank liquidity, as measured by the ratio of loans to deposits, was associated with lower rates on new loans.

Among the indicators of portfolio quality, the higher the rate of delinquencies in the bank's portfolio (total delinquencies, both agricultural loans and other loans), the lower the rate charged on new loans. Similarly, banks with a higher rate of net charge-offs closed new farm loans with significantly lower rates of interest. However, both of these indicators are difficult to interpret because they are backward-looking, while new loans necessarily reflect the bank's assessment of the borrowers' prospects in the future.

The analysis was then extended to measure the spread relationship over time by fitting the regression described above to data for each of the 20 quarters in the time period. (The results are available from the authors on request.) The resulting time patterns between risk classes 2–5 and class 1 are shown in Figure 1. The patterns conform closely to each other and, while varying by quarter, tend to consistently follow the major ups and downs. Similar to the regression parameters in Table 5, the spreads between classes 3 and 4 are consistently low, perhaps reflecting the higher concentrations in these classes. Wider spreads occur at the higher and lower classes. As might be expected, fluctuations in the spread for the most risky loans were much wider than those on other loans, with notable spikes in 1999, 2001, and 2002. Thus, the risk-adjusted pricing on loans which was evident from Table 5 for the entire time period also held on a quarterly basis, including a small but sustained margin between rates on risk classes 3 and 4 loans.

Figure 2 compares the time pattern of spreads between the lowest and highest risk classes on the STBLF survey to movements in the spread between speculative grade issues and those rated BAA in the corporate credit markets. Adjusting for the differences in scales between the two vertical axes, the bank spreads generally were a couple of percentage points less than the corporate market spreads. In contrast, however, the corporate spreads tended to increase over the 20 quarters, reflecting weaker economic conditions and an increasing level of defaults on corporate bonds during 2000–2002. High government payments helped to reduce repayment difficulties in the farm sector.

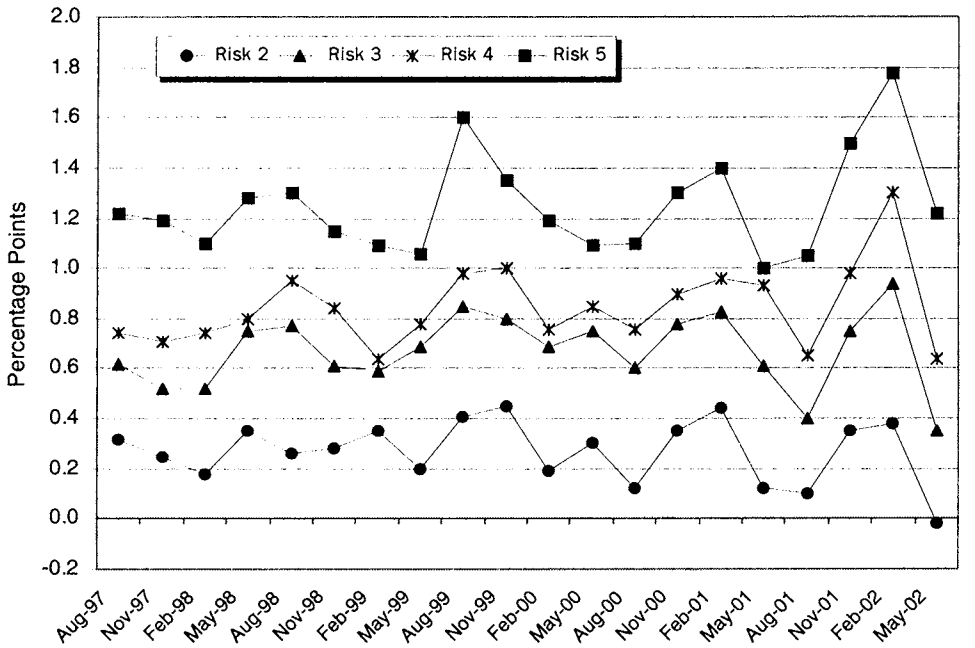


**Figure 1. Rate Spreads Among Risk Classes Relative to Class 1 Rates, August 1997 to May 2002**

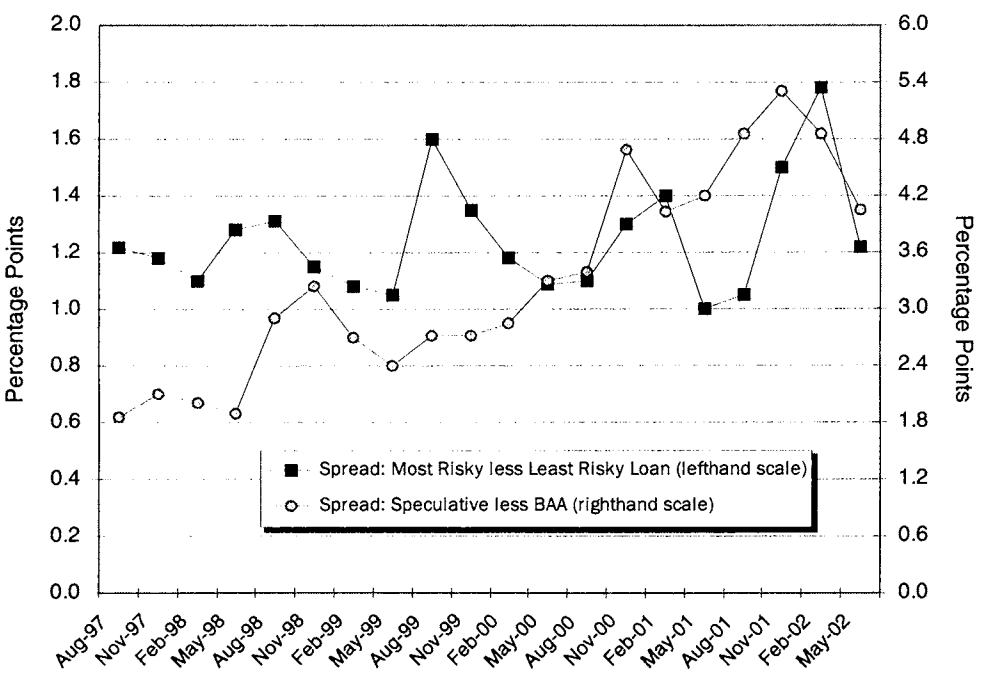


**Figure 2. Spread Patterns Between Most and Least Risky Loans and Between BAA and Speculative Grade Corporate Bonds, August 1997 to May 2002**

The parameters on nonprice variables in the quarterly regressions largely maintained the same signs, significance, and size as observed in Table 5. An interesting exception involved the variables representing loan duration (i.e., callability, prepayment, and repricing). Each of these parameters switched signs during the time period. Until 2001, the inclusion of a call provision came with an interest rate that was about 30 basis points higher. During this time, about one-quarter of the sampled loans carried call provisions. In early 2001, the proportion of sample loans with call provisions declined to about 15%, and a call provision on average reduced the loan rate by about 20 basis points. This switch in sign came as short-term rates were falling sharply in the general economy, suggesting lenders were easing terms on loans to bolster demand. In contrast, the sign and significance of the prepayment coefficient had shown no pattern until 2002, when a prepayment penalty began to coincide significantly with loan rates that were nearly one percentage point higher.

In the summer of 2000, the average number of days until the loan could be repriced fell sharply in the survey. In addition, before that time, a longer repricing period was associated with significantly lower rates. By later in 2001, however, fixing the rate for an additional month added about 10 basis points to the loan rate. This effect was highly significant.

## Concluding Comments

As suggested by the data presented here, among the smaller community banks that provide a substantial portion of farm loans, the prevalence of risk rating systems changed little during the five-year (1997–2002) sample period. Nevertheless, a sizeable volume of farm lending comes from commercial banks and is carried out utilizing rating systems that enable banks to price the perceived riskiness of their loans. Such risk-adjusted pricing occurs within a framework where loan rates also reflect adjustments for a host of nonprice terms, including security, commitments, call provisions, prepayment penalties, repricing intervals, and maturity. The resulting spreads between loans rated as minimal risk and those of high risk change over time in a pattern that is broadly consistent with quality spreads in corporate credit markets. Thus, the risk and other pricing characteristics of farm loans largely parallel those of nonfarm business loans.

The future will likely bring wider use of dual rating systems (frequency of default by borrowers and severity of default associated with loan transactions), as well as closer linkages between loan pricing, credit risk, economic capital, and risk-adjusted returns on capital. The systematic pricing practices on farm loans found in this study thus provide a benchmark to future research on loan pricing as the structure and managing of banks' credit risks continue to evolve. Considerations especially important in future research are: (*a*) the calibration between risk premiums in loan rates and probabilities of default, (*b*) loss-given-default and expected losses on individual loans, and (*c*) implications for the level and allocation of economic capital needed to cover the credit risks added by different types of loans. Also warranting consideration is the management of changes in spreads over time and in relation to major changes in economic and financial market conditions.

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# Economic Analysis of the Standard Reinsurance Agreement

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## Abstract

An economic analysis is presented of the Standard Reinsurance Agreement (SRA), the contract governing the relationship between the Federal Crop Insurance Corporation and the private insurance companies that deliver crop insurance products to farmers. The paper outlines provisions of the SRA and describes the modeling methodology behind the SRA simulator, a computer program developed to assist crop insurers and policy makers in assessing the economic impact of the Agreement. The simulator is then used to analyze how the SRA affects returns from underwriting crop insurance. The results are presented in aggregate and also at the regional and individual company levels.

*Key words:* crop insurance, policy analysis, risk modeling, Standard Reinsurance Agreement

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Risk sharing between private insurance companies and the government has been an integral part of the federal crop insurance program since 1981. The Federal Crop Insurance Act of 1980 encouraged the Federal Crop Insurance Corporation (FCIC) to privatize functions of the crop insurance program "to the maximum extent possible." A key component of the 1980 legislation was the enlistment of private insurance companies to not only sell and service crop insurance policies, but for the first time to share the risks on the policies they write. By 2001, crop insurance companies were writing policies with a total premium of almost $3 billion and retaining risks on almost $2.4 billion in premiums through the Standard Reinsurance Agreement (SRA) with the FCIC (Glauber and Collins, 2002).

From the outset, the role of the private sector in risk sharing has been controversial. Despite underwriting losses on crop insurance policies totaling $2.3 billion between 1981 and 1990, reinsured companies recorded underwriting profits in 7 of the 10 years, contributing to the total of $110 million in underwriting profits over the period (U.S. General Accounting Office, 1992). Reinsured companies argued that the poor actuarial performance of the program during the 1980s was, in part, due to inadequate premium rates set by FCIC, and they were reluctant to share in risks over which they felt they had little control. However, criticism by the U.S. General Accounting Office and others prompted Congress to require reinsured companies to bear more risk through the SRA. The 1992 SRA and subsequent reinsurance agreements have exposed the reinsured companies to substantially more risk, but also have allowed a greater

sharing of underwriting gains (Glauber and Collins, 2002).

Net underwriting gains[1] to the reinsured companies totaled almost $1.5 billion over 1997 through 2001, or about 16.6% of retained premium (Glauber and Collins, 2002). While the size of the net underwriting gains in this period can be largely attributed to the amount of premium and to the nearly ideal crop growing conditions in most regions of the United States, the gains have attracted criticism from watchdog agencies such as the U.S. General Accounting Office and the USDA's Office of Inspector General. In its fiscal year 2003 budget proposal, the Bush Administration concluded that the crop insurance companies had "experienced a windfall," and proposed capping underwriting gains at 12.5% (USDA, 2002, p. 28). Crop insurance companies responded by claiming the proposal "demonstrated a lack of understanding about how crop insurance works" (Shey, 2002) and predicted the proposal would cripple the crop insurance delivery system (American Association of Crop Insurers, 2002).

The most recent version of the Standard Reinsurance Agreement (the 2005 SRA) has been renegotiated and went into effect in 2004, although the structure of the agreement and its major provisions remained largely unchanged from the previous 1998 version.

While there has been much research on the federal crop insurance program, most of the focus has been on how insurance affects producer-level risk and the demand for crop insurance. Research on the reinsurance agreement has focused largely on the use of contingency markets such as futures and options as alternatives to traditional reinsurance (Miranda and Glauber, 1997; Mason, Hayes, and Lence, 2003; Turvey, Nayak, and Sparling, 1999). An exception is a study by Ker and McGowan (2000) who investigate the ability of crop insurance companies to adversely select against the FCIC. Using a stylized model of the SRA which considered wheat yield distributions in 57 Texas counties, they demonstrated that companies could increase expected underwriting gains by ceding more risk to the FCIC in those years where ex ante projections of wheat yields suggested potential crop insurance losses. Yet, while their research provides insight into how companies may increase underwriting gains through the SRA, their empirical findings are limited in scope.

Crop insurance companies typically write policies in more than one state, and several operate nationwide. Expected underwriting gains depend on the underlying crop yield distributions across commodities and regions and also on the structure of the SRA. Changes in the latter can have significant effects on the distribution of underwriting gains and implications for how companies can best maximize returns.

In this paper, we develop a simulation model of the SRA. Using historical data on yields and insurance losses for each crop reporting district, crop, and insurance product, we construct distributions of returns on the book of business resulting from underwriting crop insurance. The effect of SRA on underwriting gains and losses[2] is then analyzed by comparing rates of return at various levels of aggregation before and after SRA is applied.[3] In particular, an attempt is made to quantify changes in expected gains and variability of return due to SRA

[1] *Gross* underwriting gains, or simply underwriting gains, are the amount by which premiums collected exceed indemnities paid. In this article, *net* underwriting gains are gains adjusted according to the SRA.

[2] Underwriting losses can be defined as negative underwriting gains.

[3] For purposes here, the terms "before (or without) SRA" and "after (or with) SRA" refer solely to situations before and after provisions of SRA are applied to realized gains/losses, respectively, in a given reinsurance year. We do not attempt to make a comparison between the current situation and the ones where SRA does not or did not exist.

first for the whole book of business, and then in selected individual states and for individual companies. We also attempt to identify factors that affect the magnitude of these changes at the individual company level.

## The Standard Reinsurance Agreement (SRA)

### Overview

The FCIC provides reinsurance to private companies that deliver crop insurance products under the terms of SRA, which applies uniformly to all insurance companies. The Risk Management Agency (RMA) administers crop insurance and reinsurance programs on behalf of the FCIC. The SRA is periodically renegotiated, although there is no preset renegotiation schedule. In the past, the renegotiation timeframe has been mandated by acts of Congress. In particular, the 2000 Agricultural Risk Protection Act (ARPA) provided for FCIC to renegotiate the SRA at least once during the 2001 through 2005 reinsurance years. Therefore, FCIC renewed the 1998 SRA through the 2004 reinsurance year (which ended June 30, 2004), and initiated negotiations of a new agreement in early 2004. The final version of the new SRA was approved in June of 2004, and went into effect for the 2005 reinsurance year on July 1, 2004.[4]

At the time the research reported in this paper was conducted, no data were available for 2005 or subsequent reinsurance years. Our research has been based on historical data through 2001 and models the SRA then in existence, i.e., the 1998 version. However, the presented results also apply to the 2005 SRA, since the 1998 SRA structure remained essentially unchanged. The major provisions of the 2005 SRA, as well as differences between it and the 1998 SRA, are presented next, along with a discussion of how these changes might affect our results.

### Major Provisions

Reinsurance under the SRA comes in two forms: proportional and nonproportional. The proportional reinsurance allows the companies to cede a proportion of their liability in exchange for an equal proportion of the associated premiums, by transferring a share of their business to the FCIC. Nonproportional reinsurance is then applied to the remaining or *retained* portion of companies' business.

A company operates under the SRA by allocating each of its crop insurance policies[5] into one of seven reinsurance funds: a single Assigned Risk Fund (ARF) and Developmental and Commercial Funds, each of which is further subdivided according to insurance product class (CAT,[6] Revenue, and All Other Plans[7] Funds). The reinsurance funds differ in the required minimum retention rates—the proportion of total premium a company must retain through the proportional reinsurance—and in the nonproportional shares of gains and losses received or paid by the companies on retained business.

Under the 2005 SRA, the ARF has the lowest required retention rate (15% to 25%) and the smallest shares of potential gains and losses on retained business, which makes it the primary designation for high-risk contracts. The SRA also establishes limits on the maximum proportions of a company's business that can be allocated to the ARF. Depending on the particular state, these "cession limits"

[4] The text of the 2005 SRA is available online from the RMA website (www.rma.usda.gov).

[5] While companies are allowed to allocate policies on an individual basis, they may choose to make allocation decisions at higher levels of aggregation, e.g., allocate all policies in a county in the same fund. SRA does not regulate or limit such allocation decisions by individual companies.

[6] Catastrophic coverage level: 50% of expected yield indemnified at 55% of expected price.

[7] All other plans are mainly "additional" or "buy-up" yield insurance with coverage levels greater than CAT.

are set to 75%, 50%, or 25% of the company's business in a state. Under the 1998 SRA, the cession limits to Assigned Risk Funds varied from 10% to 75%, while the required retention rate was set to 20% for all states. While these changes potentially may lead to different patterns of policy allocation across reinsurance funds in the future, they do not change the effect of nonproportional reinsurance, which is the main focus of the current investigation.

The Developmental and Commercial Funds have higher minimum retention requirements (35% and 50%, respectively) and allow companies to retain up to 100% of the premiums in return for higher potential net underwriting gains and losses. The parameters of these two funds remained the same under both the 2005 SRA and the 1998 SRA.

The nonproportional shares of gains and losses are outlined in Table 1. The shares of losses paid by the companies and paid by FCIC vary according to the loss ratio[8] of the companies' retained business calculated at the state level. As the loss ratio increases, FCIC assumes a larger fraction of a company's losses up to 100% of the portion of losses in excess of 500% of total retained premium (stop-loss provision). In the case of underwriting gains (loss ratio less than 1), FCIC claims a larger fraction of the gains as the loss ratio decreases.

The shares of gains and losses are structured so that for the same absolute values of gains/losses, the companies keep a higher share of gains than losses. This is illustrated in Figure 1, which shows the net (after SRA is applied) versus gross (before SRA is applied) loss ratios for the All Other Products Funds. For example, if the realized loss ratio in Commercial Fund for all other products is 0.70 (realized gain of 30%), the company keeps 94% of gains, i.e., its net gain after SRA is 28.2%. At the same time, if the realized loss ratio in the same fund is 1.3 (realized loss of 30%), the company is responsible only for 50% of the losses, i.e., its net loss after SRA is 15%. The same holds true for other ranges of loss ratios (see Table 1). Thus, the SRA's nonproportional reinsurance effectively transforms the loss ratio of the company on its retained business. Furthermore, the decreasing shares of gains kept and losses borne by the companies result in narrowing of loss ratio distributions (as demonstrated in Figure 2 later in the paper).

The shares of gains and losses, which are the key components of this analysis, remained the same under the 2005 SRA as they were under the 1998 SRA, allowing our results to be extended to the new version of the Agreement.

The 2005 SRA also added a "retained net book quota share" form of reinsurance under which each company is required to cede to FCIC 5% of its cumulative underwriting gain or loss defined as net underwriting gains or losses in all states after the proportional and nonproportional reinsurance provisions of the SRA are applied. While this provision was not modeled under the 1998 SRA, its effect on the results would be fairly straightforward.

## Modeling Methodology

The objective of the SRA model is to simulate distributions of rates of return[9] from underwriting crop insurance. The realized rates of return (i.e., before the SRA is applied) are driven by gross underwriting gains or losses defined for modeling purposes as the difference between the premiums collected and indemnities paid. The rates of return after the SRA is applied are determined by particular realizations of companies' loss ratios at the state level and the SRA parameters (retention rates, breakpoints, and shares). Therefore, in order to analyze the effect of SRA on the rates of return, it

[8] Loss ratio is indemnity divided by premium.

[9] Rates of return are defined as the ratios of underwriting gains (losses) to gross premiums.

**Table 1. Companies' Shares in Underwriting Gains and Losses Under SRA**

| Reinsurance Fund | Gains, by Insurance Plan | | | Losses, by Insurance Plan | | |
|---|---|---|---|---|---|---|
| | CAT | Revenue | All Other | CAT | Revenue | All Other |
| | *– Loss Ratio Between 65% & 100% –* | | | *– Loss Ratio Between 100% & 160% –* | | |
| Commercial | 75.0% | 94.0% | 94.0% | 50.0% | 57.0% | 50.0% |
| Developmental | 45.0% | 60.0% | 60.0% | 25.0% | 30.0% | 25.0% |
| Assigned Risk | ---------- | 15.0% | --------- | ---------- | 5.0% | ---------- |
| | *– Loss Ratio Between 50% & 65% –* | | | *– Loss Ratio Between 160% & 220% –* | | |
| Commercial | 50.0% | 70.0% | 70.0% | 40.0% | 43.0% | 40.0% |
| Developmental | 30.0% | 50.0% | 50.0% | 20.0% | 22.5% | 20.0% |
| Assigned Risk | ---------- | 9.0% | ---------- | ---------- | 4.0% | ---------- |
| | *– Loss Ratio Less than 50% –* | | | *– Loss Ratio Between 220% & 500% –* | | |
| Commercial | 8.0% | 11.0% | 11.0% | 17.0% | 17.0% | 17.0% |
| Developmental | 4.0% | 6.0% | 6.0% | 11.0% | 11.0% | 11.0% |
| Assigned Risk | ---------- | 2.0% | ---------- | ---------- | 2.0% | ---------- |

*Note:* FCIC keeps the portions of underwriting gains or assumes the ultimate net losses in excess of companies' shares as determined in the table. In addition, FCIC assumes 100% of the amount by which companies' retained losses exceed 500% of the retained net book premium in a given state and fund for a given reinsurance year.

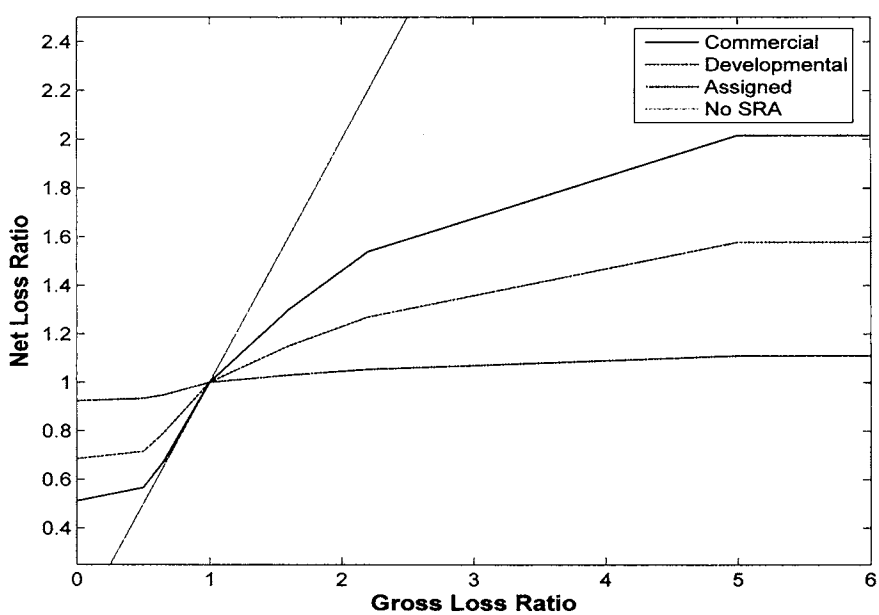


**Figure 1. Net (after SRA is applied) vs. Gross (before SRA is applied) Loss Ratios by Reinsurance Fund (commercial and developmental funds are shown for "all other plans")**

is necessary to model the distribution of loss ratios by state and fund for each company reinsured by the FCIC.

The straightforward approach to deriving distributions of loss ratios from historical series of indemnities and premiums is not applicable due to the changing nature of the crop insurance program and data limitations. First, the number of contract types available under the crop insurance program has increased dramatically since 1980, with a large portion of products introduced in or after 1994. Therefore, historical loss data are simply not available for many contracts prior to 1994. Second, program participation has also increased over the last two decades both in terms of the acreage insured and coverage levels selected by the producers. This in turn led to a broader pool of insured risk and decreasing variation in indemnities. Third, composition and geographical distribution of contracts in participating companies' books of business have changed over time. The companies have also changed allocation of their books of business across reinsurance funds. Finally, premium rates[10] have changed over time, thus affecting historical realizations of companies' gains and losses. Instead, it was assumed that the loss costs by crop reporting district,[11] crop, and insurance product observed over the historical period (1981–2001) were generated by stationary data-generating processes which are uniform across companies and reinsurance funds.

Historical loss costs at the district level are available for 1981–2001 for selected Actual Production History (APH)[12] yield contracts but only in aggregate, thus providing no information about the distribution of loss costs for specific APH yield contracts, or other contracts such as CAT and revenue products. The loss costs for individual products, however, can be recovered or simulated from data on yields and prices.

The distributions of district-level yields can be derived from historical yield data. However, the aggregate yields are not necessarily representative of yields experienced by insurance buyers. Therefore, distributions of individual yields within each district are also modeled by imposing a parametric distribution with the parameters calibrated so as to match the historical insurance experience reflected in the aggregate loss costs data. The calibrated individual yield distributions along with price models then allow one to simulate distributions of loss costs for all individual products included in the model.

The simulated distribution of loss costs for each district, crop, and insurance product can be combined with the data on liabilities and premium rates for the base year (2001) and aggregated to derive distributions of loss ratios for each company by state and reinsurance fund. The derived distributions of the loss ratios can then be used in combination with the SRA parameters to compute expectations and standard deviations of the rates of return by company, state, and/or reinsurance fund.

While there are more than 20 types of products available for more than 100 crops, the lack of adequate data and the limited scope of some programs do not allow us to incorporate all of them into a simulation model. For our analysis, six crops and five major types of insurance products are included in the model. The crops are barley, corn, cotton, soybeans, grain sorghum, and winter wheat.[13] The insurance products are (*a*) CAT; (*b*) Actual Production History (APH) yield insurance, Crop Revenue Coverage (CRC), and Income Protection (IP) (each at 50%, 55%, 60%, 65%, 70%, 75%, 80%, and 85% coverage levels); and (*c*) Revenue Assurance (RA)

[10] The premium rate of a contract is a ratio of its premium to the associated liability.

[11] A crop reporting district (CRD) is a statistical unit intermediate between a county and a state. Each state is typically split into nine or ten CRDs, and each CRD typically includes eight to twelve counties.

[12] APH is the type of farm yield insurance contract with the longest historical series.

[13] These crops accounted for 0.8%, 42.7%, 13.2%, 27.3%, 2.2%, and 13.7% of the total premiums included in the model, respectively.

(at 65%, 70%, 75%, 80%, and 85% coverage levels). Together, these combinations of crops and products encompass about 65% of the total FCIC liabilities in 2001.[14]

District-level yields for the six crops over the historical period are available from NASS. A simple log-linear time trend is fitted for each crop and district:[15]

$$(1)\quad \log(y_t^{tr}) = \alpha_0 + \alpha_1(t - 1980),$$
$$t = 1981, \ldots, 2001.$$

The district yields detrended to 2001 equivalents are calculated as follows:

$$(2)\quad y_t^{det} = \frac{y_t}{y_t^{tr}} y_{2001}^{tr}, \quad t = 1981, \ldots, 2001,$$

where $y_t$ are the observed yields and $y_t^{tr}$ are the corresponding yield trends. The detrended yield observations are then used to construct an empirical distribution of district yields (Goodwin and Ker, 1998; Ker and Goodwin, 2000; Ker and Coble, 2003) for the base year (2001) by assigning equal probabilities[16] $1/n_y$ ($n_y = 2001 - 1981 + 1$) to each realization of the district yield $y_t^{det}$ ($t = 1981, \ldots, 2001$). Such an approach allows us to capture correlations between yields in different districts and for different crops in a simple and efficient way without imposing additional distributional properties such as positive skewness.

Since indemnities of all insurance products included in the model depend on farm-level rather than district-level yields, the distribution of yields within the district must also be modeled. For a given realization of district yield ($y_d$), it is assumed the individual farm's yield ($y_f$) is lognormally distributed[17] around the district yield so that

$$(3)\quad \log(y_f) = \log(y_d) + \varepsilon, \quad \varepsilon \sim N(\mu, \sigma^2),$$

where the distribution parameters $\mu$ and $\sigma^2$ may depend on the district yield (Miranda, 1991). This approach preserves the empirical yield distribution present in the detrended district yield series, but also reintroduces the variability of farm-level yields lost in averaging to the district level (Mason, Hayes, and Lence, 2003; Schnitkey, Sherrick, and Irwin, 2003). Under these assumptions, the loss cost for an APH product with the coverage level $\eta$ and APH average yield $\bar{y}$ can be calculated as

$$\mathbf{E}_\varepsilon \max\left\{0, 1 - \frac{y_f}{\eta \bar{y}}\right\}.$$

For each district and crop, the historical loss costs are available in aggregate for selected products (APH 35% and 50%, 55%, ..., 85%) as well as data on liabilities by individual product. This allows us to calibrate the parameters of the farm-level yield distributions in (3) whereby the loss costs recovered from these distributions and then aggregated with corresponding liability weights match the observed aggregate loss costs as closely as possible. Similar to the approach adopted by Mason, Hayes, and Lence (2003), we attempt to add enough noise to the district-level yields to replicate the observed aggregate loss costs. The calibration is performed individually for each district, crop, and year, so as to reflect possible differences in within-district yield variabilities.[18]

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[14] While it may seem that the model leaves out a significant portion of the FCIC portfolio, a major part of it consists of specialty crops concentrated mainly in California and Florida. Outside of these two states, the proportion of liability covered by the model is about 75% for the base year (2001).

[15] Note that this procedure does not impose any distributional assumptions on the residuals but is used only to remove the central tendency.

[16] We recognize that yield series of only 21 years may (and probably do) bias the results to some extent. However, the major limiting factor here is the lack of corresponding loss cost data for crop insurance products, and thus using longer yield series would not improve the simulations.

[17] Weibull and gamma distributions were also used to model the individual yields. The results were similar to those obtained with lognormal distribution; however, lognormal distribution performed better in matching historical aggregate loss costs, i.e., minimizing the criterion in (4).

[18] Variability of farm-level yields does not have to be the same in different districts, or for different crops. In addition, higher realizations of district-level yields tend to be associated with less variability at the individual level, and vice versa, i.e., yield variability may change from year to year.

Formally, for a given district, crop, and year, let $LC_{sim}(i_p \mid \mu, \sigma)$ be the simulated loss cost for the APH product $i_p$ for the given values of parameters $\mu$ and $\sigma$ of the distribution of farm-level yields in (3). Further, let $LC_{hist}^{agg}$ be the historical aggregate loss cost, let $B \subseteq \{1, \ldots, n_p\}$ be the index subset of APH products included in the aggregate loss cost data, and let $L_{hist}(i_p)$ be the historical liabilities for products in $B$. The aggregate simulated loss cost can then be calculated as

$$LC_{sim}^{agg}(\mu, \sigma) = \frac{\sum_{i_p \in B} L_{hist}(i_p) \times LC_{sim}(i_p \mid \mu, \sigma)}{\sum_{i_p \in B} L_{hist}(i_p)},$$

and the parameters $\mu$ and $\sigma$ of farm-level yield distribution in (3) can then be calibrated by solving

$$(4) \quad \min_{\mu,\sigma} \left| LC_{hist}^{agg} - LC_{sim}^{agg}(\mu, \sigma) \right|$$
$$\text{s.t.: } \mathbf{E}_\varepsilon y_f = y_d.$$

The constraint in (4) reflects the fact that the district-level yields are simply averages of individual yields within the district.

Once the parameters of farm-level yield distributions are calibrated, it is assumed that they correctly represent the variability of within-district yields for the specific crop, district, and year, and thus can be used to simulate the loss costs for all other products included in the model. In addition to yields, distributions of harvest-time prices are required to calculate loss costs for revenue products. The distribution of intra-seasonal prices was modeled[19] for each crop as

$$(5) \quad \log(p_h) = \log(p_b) + \alpha\left(\log(y_{nat}) - \log(\bar{y}_{nat})\right) + z,$$

where $p_h$ is the harvest price, $p_b$ is the base (projected) price, $y_{nat}$ is the detrended national yield, $\bar{y}_{nat}$ is the long-term average detrended national yield, $\alpha$ is the elasticity parameter capturing correlation between national yields and prices, and $z$ is a random shock that reflects additional price variability independent of $y_{nat}$ and is distributed normally with zero mean and some variance $\sigma^2$.

For practical purposes, national yields data were collected from NASS and detrended according to (1)–(2). The values of the elasticity parameters $\alpha$ were chosen to represent historically observed correlation between national yields and prices. The base prices and the variances of harvest prices were obtained from RMA publications[20] and reflected contemporary market information available prior to the 2001 planting season (Table 2).

By combining distributions of yields (3) calibrated according to (4) with the price distributions in (5), we can derive the distributions of loss costs for all districts, crops, and products included in the model. Data on base year premium rates and liabilities can then be used to aggregate these distributions and arrive at the premium rates and distributions of loss costs by state, company, and reinsurance fund. The provisions of the SRA (Table 1) can then be applied to arrive at the distributions of adjusted rates of returns aggregated by companies, states, and reinsurance funds. A formal presentation of the aggregation procedure and derivation of distributions of rates of return can be found in Vedenov (2001).

[19] Historical series could also be used to estimate variability of prices. However, the historical price series are often distorted by nonstationarity, changing farm policies and support programs, inflation, etc. (Zulauf and Blue, 2003).

[20] The base prices are established and published by RMA prior to beginning of the planting season, and are typically based on monthly averages of corresponding futures prices (USDA/RMA, 1999). The total variances are monthly averages of implied volatilities derived from option contracts matching the futures contracts used to derive the corresponding base prices. Since the random shocks $z$ in equation (5) are assumed to be independent of corresponding yields, the shock variance $\sigma^2$ for each crop can be calculated as a difference between the total variance of the harvest price (Table 2) and the sample variance of the national yield (NASS data).

**Table 2. Parameters of Price Models**

| Crop | Base Price[a] ($p_b$) | Elasticity ($\alpha$) | Total Variance[b] [Var($p_h$)] |
|---|---|---|---|
| Barley | 2.07 | -0.5 | 0.0213 |
| Corn | 2.44 | -0.5 | 0.0213 |
| Cotton | 0.66 | -0.5 | 0.0132 |
| Soybeans | 5.23 | -0.5 | 0.0144 |
| Sorghum | 2.32 | -0.5 | 0.0213 |
| Wheat | 3.41 | -0.5 | 0.0215 |

[a] Base prices are established and published by RMA prior to the beginning of the planting season and are typically based on monthly averages of corresponding futures prices (USDA/RMA, 1999).

[b] The total variances are monthly averages of implied volatilities derived from option contracts matching the futures contracts used to derive the corresponding base prices. Since the random shocks $z$ in equation (5) are assumed to be independent of corresponding yields, the shock variance $\sigma^2$ for each crop can be calculated as a difference between the total variance of the harvest price (given in the table) and the sample variance of the national yield (NASS data).

## Results

In order to analyze the effect of the SRA on loss ratios and thus rates of return, data on companies' books of business, allocations, and retention rates in 2001 have been used to simulate the distributions of the aggregate loss ratios before and after the SRA is applied.[21] Figure 2 shows these distributions by fund and in aggregate.[22] The distributions of loss ratios within individual reinsurance funds before the SRA is applied (dotted lines) reflect the difference in the level of protection provided by each of them, and thus allocation of business across funds. The Commercial Fund tends to attract less risky contracts, while the Developmental Fund and especially ARF are used for more risky business. The distributions of loss ratios after the SRA is applied (solid lines) are visibly narrower and shifted to the left. Recall that the narrowing effect is caused by decreasing shares of gains kept and losses borne by insurance companies built into the SRA structure (Table 1).

Comparison of distribution moments also indicates that the reinsurance provided by the SRA lowers both the expected values and variability of loss ratios (Table 3). As expected, the reinsurance provisions of the ARF result in the largest decrease in variability of loss ratios (93%) as well as the largest decrease in their expected values (11.8%). The reinsurance provisions of the Developmental and Commercial Funds decrease the variability of loss ratios to a lesser extent, but also result in lower decreases in the expected values.

Since most companies underwrite crop insurance in more than one state, it is important to consider how SRA affects returns at the regional level. Presented in Table 4 are expected underwriting gains[23] before and after SRA is applied for the top 20 states in terms of gross premiums, which together cover about 90% of the total gross premiums included in the simulation. Without reinsurance provided by the FCIC, underwriting of crop insurance would be profitable only in nine mostly Midwestern and Plains states. The SRA significantly improves the expected gains in all 20 states, making all but three of them profitable. Therefore, it comes as no surprise that even the states characterized by high expected losses without SRA attract more than one insurance company.

Increases in the overall expected gains might be achieved by ceding especially risky contracts to FCIC. Analysis of premium retention and fund allocation at the state level (Table 4, columns 4 and 6) confirms that in most cases states with expected losses without SRA tend to have lower proportions of business retained and higher proportions placed in the ARF.

[21] Once again, note that the goal of the present study is to separate the effect of SRA on the rates of return ceteris paribus, rather than make any conclusions about the world where SRA is not available. Such an analysis, however, is within the possibilities of the presented model and may be a focus of future research.

[22] For presentation purposes, empirical distributions have been smoothed using a kernel-smoothing procedure with variable-bandwidth Epanechnikov kernel (Härdle, 1991).

[23] The expected gains are the means of corresponding distributions produced by the simulation model.

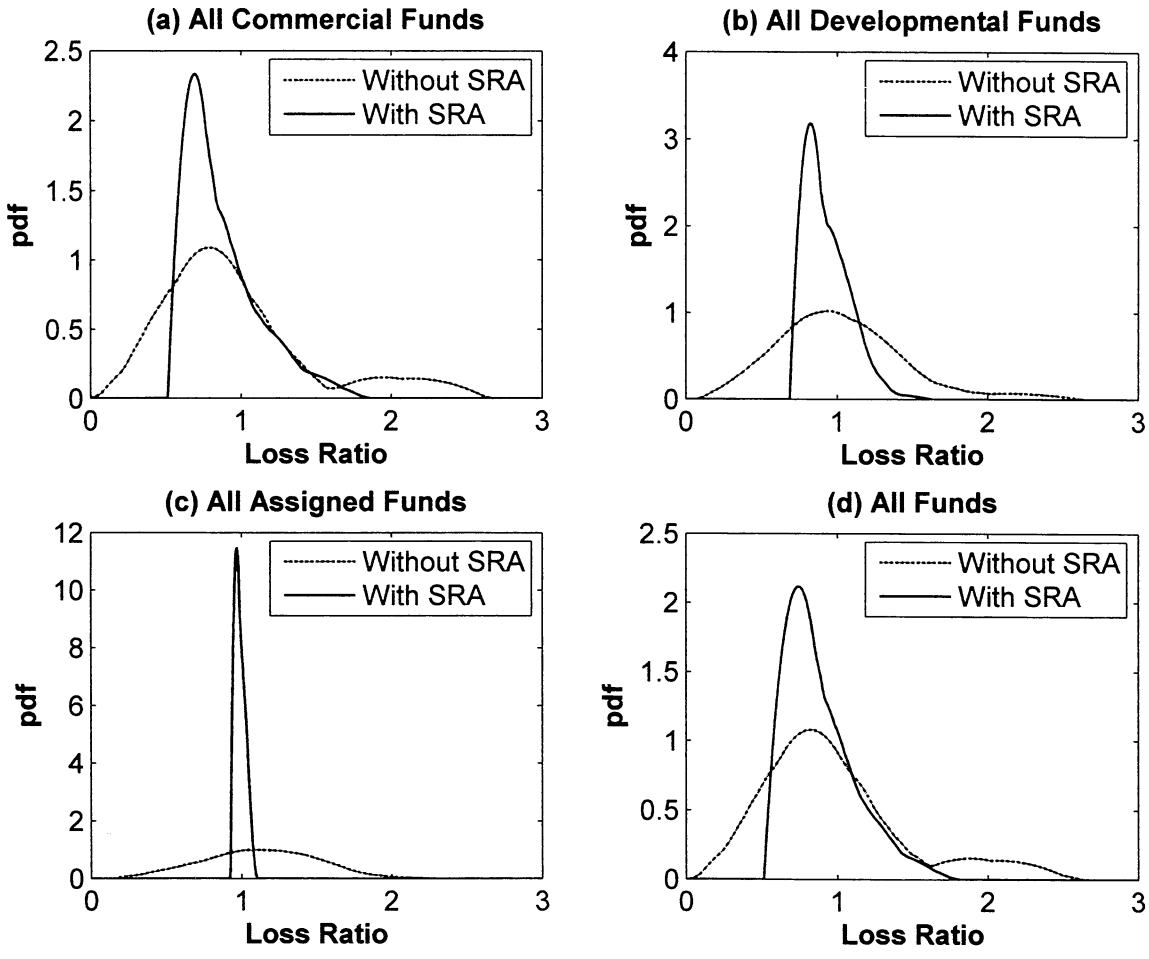


**Figure 2. Effect of SRA on Distribution of Loss Ratios for the Aggregated Book of Business: (a) all commercial funds, (b) all developmental funds, (c) assigned risk funds, and (d) all funds**

**Table 3. Distributions of Aggregate Loss Ratios Before and After SRA Is Applied, Sample Statistics**

| | Before SRA | | After SRA | | Percent Change | |
|---|---|---|---|---|---|---|
| **Reinsurance Fund** | **Mean** | **Std. Dev.** | **Mean** | **Std. Dev.** | **Mean** | **Std. Dev.** |
| All Commercial | 0.953 | 0.468 | 0.866 | 0.205 | -9.1% | -56.3% |
| All Developmental | 1.025 | 0.374 | 0.927 | 0.100 | -9.5% | -73.3% |
| All Assigned | 1.121 | 0.307 | 0.988 | 0.020 | -11.8% | -93.6% |
| All Funds | 0.973 | 0.438 | 0.882 | 0.177 | -9.3% | -59.6% |

A notable exception is Texas, which has a small expected underwriting gain without SRA, yet has a relatively high percentage of business in the ARF. A possible explanation is that due to the variation of growing conditions within a state, underwriting crop insurance may be quite profitable in some areas or for some crops, while unprofitable for other areas or crops. Aggregated at the state level, the losses cancel out most of the gains, but individual companies may have business concentrated mostly in the low-return areas, and thus tend to use ARF to a higher extent.

The net effect of the SRA on expected gains differs significantly by state. The general tendency is the lower the gain before SRA is applied, the higher the change in expected gain due to reinsurance. However, there are several exceptions to this rule on both sides. For example, Oklahoma, Georgia, and Wisconsin experience rather modest increases in the expected gains compared to the levels of gains before the SRA is applied. In fact, Oklahoma is barely profitable even after the SRA provisions are applied. In contrast, changes in expected gains in Kansas and Texas are fairly high, even though their returns without SRA are not nearly as bad. Substantial increases in expected gains are also observed in Minnesota and Illinois, where underwriting crop insurance would be profitable even without the reinsurance.

Expected underwriting gains at the company level are presented in Tables 5 and 6. In particular, Table 5 reports returns from underwriting crop insurance at the company level before SRA is applied. To analyze the effect of geographical diversification on underwriting returns, we calculated two measures of diversification for each company's crop insurance portfolio. The first is the Herfindahl-Hirschman Index (HHI), a commonly accepted measure of market concentration (Tirole, 1988, p. 221) which can also be used as a general measure of diversification. The index was calculated as the sum of the squared shares of a company's premium in each state. The lower the HHI, the more diversified is the portfolio.[24] The second measure is the proportion of each company's gross premiums in regions that we defined based on expected underwriting gains before SRA: Region 1, comprised of states with negative expected underwriting gains before SRA; and Region 2, comprised of states with positive expected underwriting gains before SRA (Table 4).

Diversification as measured by the HHI does not seem to be directly related to the expected returns from underwriting crop insurance, as companies with roughly the same HHI may have dramatically different returns (e.g., Company 2 and Company 12). Variability of returns appears to be slightly more related to the HHI, with lower HHI corresponding to lower standard deviations of returns without SRA, although not without exceptions (e.g., compare Companies 16 and 19). These results are fairly logical, since the HHI does not take into account returns from individual states or correlation between crop yields across states, but rather reflects overall composition of companies' portfolios.

[24] The actual numbers of states in which companies underwrite crop insurance are withheld to protect the identities of individual companies.

**Table 4. Returns for Selected States Before and After SRA Is Applied**

| State [a] | Number of Companies | Gross Premium [b] ($ mil.) | % Premiums in ARF [c] | Retained Premium [b] ($ mil.) | % Retained | Expected Gain: Before SRA ($ mil.) | Expected Gain: After SRA ($ mil.) | Change ($ mil.) |
|---|---|---|---|---|---|---|---|---|
| Mississippi | 8 | 70.2 | 55.6% | 33.7 | 48.0% | -28.78 | -3.77 | 25.01 |
| Louisiana | 7 | 31.8 | 40.3% | 20.2 | 63.5% | -27.62 | -4.81 | 22.81 |
| Arkansas | 11 | 44.7 | 36.3% | 29.9 | 66.9% | -20.29 | -3.50 | 16.79 |
| Montana | 13 | 43.0 | 36.4% | 29.3 | 68.1% | -15.67 | 0.06 | 15.73 |
| S. Dakota | 12 | 131.8 | 15.5% | 111.9 | 84.9% | -7.51 | 7.50 | 15.01 |
| Oklahoma | 12 | 48.7 | 36.1% | 32.6 | 67.0% | -6.03 | 0.13 | 6.16 |
| N. Dakota | 13 | 134.1 | 36.9% | 92.1 | 68.7% | -4.96 | 6.82 | 11.78 |
| Georgia | 10 | 60.5 | 35.8% | 38.6 | 63.8% | -4.18 | 1.66 | 5.84 |
| Wisconsin | 9 | 37.0 | 7.6% | 34.6 | 93.5% | -3.22 | 3.39 | 6.61 |
| Missouri | 14 | 76.3 | 9.1% | 68.2 | 89.4% | -1.83 | 6.41 | 8.24 |
| Kansas | 14 | 164.4 | 13.5% | 141.9 | 86.3% | -1.81 | 9.93 | 11.74 |
| Ohio | 12 | 47.2 | 9.9% | 42.8 | 90.6% | 0.28 | 4.28 | 4.00 |
| Texas | 10 | 297.6 | 43.3% | 185.9 | 62.5% | 0.60 | 13.94 | 13.35 |
| Colorado | 13 | 40.8 | 10.5% | 37.1 | 90.9% | 3.06 | 3.90 | 0.83 |
| Indiana | 13 | 80.6 | 11.3% | 73.0 | 90.5% | 3.79 | 9.13 | 5.33 |
| N. Carolina | 9 | 39.1 | 15.0% | 32.3 | 82.6% | 3.91 | 3.71 | -0.20 |
| Illinois | 13 | 162.3 | 6.3% | 152.8 | 94.2% | 15.90 | 29.49 | 13.59 |
| Minnesota | 14 | 179.3 | 8.9% | 164.4 | 91.7% | 25.29 | 39.46 | 14.17 |
| Nebraska | 13 | 176.0 | 10.2% | 160.8 | 91.4% | 36.43 | 31.20 | -5.23 |
| Iowa | 13 | 223.8 | 5.1% | 213.9 | 95.6% | 49.01 | 51.55 | 2.54 |
| All States | 19 | 2,283.9 | 20.6% | 1,853.4 | 81.2% | 0.00 | 218.70 | 218.70 |

[a] States are sorted by the expected gains without reinsurance (column 7). Only the top 20 states in terms of gross premiums are included in the table.
[b] All premiums are calculated as a part of the simulation and are not actual premiums collected and/or retained by participating companies.
[c] ARF is Assigned Risk Fund.

**Table 5. Regional Composition of Insurance Portfolios and Returns Without SRA, by Company**

| Company [a] | Herfindahl-Hirschman Index (HHI) | % Premiums in Region 1 [b] | % Premiums in Region 2 [c] | % Premiums in ARF [d] | % Retained | Expected Rate of Return [e] | Standard Deviation [e] |
|---|---|---|---|---|---|---|---|
| 1 | 2,259 | 81.5% | 11.1% | 35.3% | 60.4% | -11.9% | 38.9% |
| 2 | 857 | 46.8% | 44.8% | 34.3% | 72.0% | -9.0% | 36.6% |
| 3 | 716 | 40.9% | 50.2% | 19.5% | 76.3% | -8.5% | 41.6% |
| 4 | 4,711 | 21.8% | 75.9% | 30.8% | 74.8% | -2.6% | 35.3% |
| 5 | 583 | 39.1% | 47.0% | 13.2% | 89.4% | -1.3% | 37.2% |
| 6 | 2,362 | 61.1% | 38.1% | 24.5% | 80.3% | -1.1% | 30.0% |
| 7 | 3,019 | 73.6% | 19.1% | 14.9% | 84.9% | -1.3% | 38.0% |
| 8 | 683 | 33.8% | 53.7% | 16.9% | 86.5% | -0.3% | 38.1% |
| 9 | 2,268 | 48.6% | 47.0% | 14.7% | 88.3% | 1.6% | 62.1% |
| 10 | 1,134 | 56.6% | 41.4% | 25.1% | 66.5% | 1.7% | 33.9% |
| 11 | 9,897 | 0.5% | 99.5% | 22.2% | 81.3% | 2.3% | 48.9% |
| 12 | 796 | 27.2% | 65.4% | 29.6% | 73.6% | 3.2% | 38.1% |
| 13 | 940 | 35.5% | 58.0% | 18.3% | 85.3% | 3.4% | 51.5% |
| 14 | 1,407 | 34.8% | 61.2% | 13.7% | 87.7% | 9.3% | 56.9% |
| 15 | 1,346 | 25.3% | 69.4% | 17.7% | 77.5% | 10.7% | 55.9% |
| 16 | 9,823 | 0.0% | 99.1% | 0.3% | 99.7% | 11.9% | 98.8% |
| 17 | 3,342 | 3.6% | 96.4% | 12.5% | 89.8% | 14.4% | 77.2% |
| 18 | 7,461 | 3.0% | 97.0% | 6.8% | 94.5% | 15.1% | 93.3% |
| 19 | 10,000 | 0.0% | 100.0% | 2.8% | 97.1% | 20.9% | 37.2% |
| All Companies | 629 | 36.3% | 54.8% | 20.6% | 81.2% | 0.0% | 39.5% |

[a] The dollar amounts of premiums are withheld and companies' names are replaced by scrambled identifiers due to the proprietary nature of data used.
[b] Region 1 (states with negative expected underwriting gains before SRA) includes MS, LA, AR, MT, SD, OK, ND, GA, WI, KS, and MO (see Table 4).
[c] Region 2 (states with positive expected underwriting gains before SRA) includes OH, TX, NC, CO, IN, IL, MN, NE, and IA (see Table 4).
[d] ARF is Assigned Risk Fund.
[e] Expected rates of return and their standard deviations are expressed as percentages of gross premiums.

The distribution of business between the identified regions, on the other hand, is found to be extremely important in determining the overall rates of return. Indeed, companies with extremely high expected losses have major portions of their business concentrated in Region 1 (states with negative expected returns without SRA) and vice versa. In other words, it is less important in how many states a company underwrites crop insurance than where it does so.

The effects of SRA on returns of individual companies are presented in Table 6. Given the crop insurance portfolios in the model base year (2001), eight out of 19 companies would experience underwriting losses without the SRA, and all companies would face extremely high variability of expected returns. The SRA increases the expected returns of all but one company and also significantly decreases the variability. The magnitude of this effect varies by individual companies; composition of companies' portfolios, once again, appears to be the most probable explanation.

While watchdog agencies and industry groups may disagree on whether the SRA generates excessive returns to companies, our analysis suggests a picture far more complicated than the one reflected in the bottom line. Gross underwriting gains are not distributed equally across states and companies. Rather, they tend to be concentrated in a handful of states where the actuarial performance has been generally good over the time period analyzed. Four states—Illinois, Iowa, Minnesota, and Nebraska—account for about two-thirds of total gross underwriting gains in the model. Companies with business concentrated in states with high returns tend to have higher rates of return than companies that underwrite crop insurance in many states. Still, the SRA provides a means by which companies can deliver insurance in states with poor expected actuarial performance. The results also suggest that any change to the SRA failing to take into account the regional aspects of the program would potentially have differential, and perhaps destabilizing, impacts on the crop insurance industry.

## Conclusion

This article presents an economic analysis of the underwriting gains and losses under the Standard Reinsurance Agreement, the contract governing the reinsurance relationship between the Federal Crop Insurance Corporation and private insurance companies that deliver crop insurance products to farmers. A simulation model is developed, using historical data on yields and insurance losses in order to simulate empirical distributions of insurance companies' loss ratios under 2001 composition of their books of business. The crucial assumption is that the historically observed loss costs, or ratios of indemnities to total liabilities, were generated by stationary data-generating processes, and thus correctly represent the true distribution of underwriting losses. A representative farmer model is used to simulate yields for any given district, crop, and year, with parameters of random yield shocks calibrated such that the simulated loss costs match the historically observed ones. The simulated distributions of loss costs are then combined with data on liabilities and retained premiums in order to arrive at distributions of loss ratios aggregated by state, company, and fund for the base year of 2001.

The simulation program is used to analyze the effect of the SRA on the distributions of loss ratios and rates of return at several levels of aggregation. The reinsurance provisions of the SRA result in both higher expected values and lower variability of returns of individual companies, thus providing an incentive to participate in underwriting crop insurance. At the regional level, the SRA makes underwriting crop insurance profitable in most of the major crop-producing states, although the magnitude of the effect varies significantly across individual states. While this analysis was performed under the 1998 version of the SRA, the results are also applicable to the recently renegotiated 2005 SRA, which did not change the provisions of the nonproportional reinsurance.

**Table 6. Rates of Return by Company Before and After SRA Is Applied**

| | Before SRA | | After SRA | | Percent Change in: | |
|---|---|---|---|---|---|---|
| Company | Expected Rate of Return | Standard Deviation | Expected Rate of Return | Standard Deviation | Expected Rate of Return | Standard Deviation |
| 1 | -11.9% | 38.9% | 3.3% | 9.0% | 15.2% | -29.9% |
| 2 | -9.0% | 36.6% | 6.6% | 10.7% | 15.6% | -25.9% |
| 3 | -8.5% | 41.6% | 6.1% | 13.2% | 14.6% | -28.4% |
| 4 | -2.6% | 35.3% | 5.4% | 10.3% | 8.0% | -25.0% |
| 5 | -1.3% | 37.2% | 9.2% | 15.8% | 10.5% | -21.4% |
| 6 | -1.1% | 30.0% | 6.6% | 10.9% | 7.7% | -19.1% |
| 7 | -1.3% | 38.0% | 6.9% | 14.9% | 8.2% | -23.1% |
| 8 | -0.3% | 38.1% | 9.5% | 14.3% | 9.8% | -23.8% |
| 9 | 1.6% | 62.1% | 11.0% | 18.2% | 9.4% | -43.9% |
| 10 | 1.7% | 33.9% | 7.5% | 10.7% | 5.8% | -23.2% |
| 11 | 2.3% | 48.9% | 8.7% | 24.2% | 6.4% | -24.7% |
| 12 | 3.2% | 38.1% | 10.1% | 13.8% | 6.9% | -24.3% |
| 13 | 3.4% | 51.5% | 11.2% | 17.4% | 7.8% | -34.1% |
| 14 | 9.3% | 56.9% | 14.9% | 19.9% | 5.6% | -37.0% |
| 15 | 10.7% | 55.9% | 14.4% | 17.5% | 3.7% | -38.4% |
| 16 | 11.9% | 98.8% | 19.8% | 35.5% | 7.9% | -63.3% |
| 17 | 14.4% | 77.2% | 18.7% | 27.7% | 4.3% | -49.5% |
| 18 | 15.1% | 93.3% | 20.2% | 32.9% | 5.1% | -60.4% |
| 19 | 20.9% | 37.2% | 19.2% | 25.2% | -1.7% | -12.0% |
| All | 0.0% | 39.5% | 9.6% | 14.0% | 9.6% | -25.5% |

*Notes:* The dollar amounts of premiums are withheld and companies' names are replaced by scrambled identifiers due to the proprietary nature of data used. All values in table are expressed as percentages of gross premiums.

The overall effects of the new SRA on underwriting returns remain to be seen. Given the relatively minor nature of changes, the adjustments are also likely to be rather minor. Changes in the session limits to the Assigned Risk Fund (ARF) may result in more business allocated to this fund in states with poor expected returns before SRA is applied. The companies may also be willing to underwrite riskier contracts overall in anticipation of their ability to pass more of the bad risk to the FCIC. Analysis of these effects may be a subject of future research as data on changes in portfolio allocation become available.

Further research may also include analysis of companies' behavior in allocating their books of business across reinsurance funds so as to maximize their underwriting gains, as well as counter-factual simulations of alternative SRA structures and reinsurance provisions.

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# Farm-Level and Macroeconomic Determinants of Farm Credit Risk Migration Rates

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## Abstract

Logistic regression techniques for panel data are used to identify factors affecting farm credit transition probabilities. Results indicate that most farm-specific factors do not have adequate explanatory influence on the probability of farm credit risk transition. Class upgrade probabilities are more significantly affected by changes in certain macroeconomic factors, such as economic growth signals (from changes in stock price indexes and farm real estate values) and larger money supply that relax the credit constraint. Increases in interest rates, on the other hand, negatively affect such probabilities.

*Key words:* demographic factors, farm credit risk migration, macroeconomic variables, ordered logit regression, random-effects model, transition probabilities

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Migration analysis, a probability-based measurement concept, has been long employed by such companies as Moodys and Standard and Poor's (S&P) in evaluating changes in the risk ratings of bonds and other publicly traded securities. The concept has been used more recently to estimate financial stress and/or default rates for commercial, agricultural, and other types of loans (Saunders, 1999; Caouette, Altman, and Narayanan, 1999; Barry, Escalante, and Ellinger, 2002).

The migration approach entails tracking an individual borrower's historic rates of movement among the lender's credit risk rating classes within a specified time period. These migration rates are used to project the credit quality of loan portfolios according to class upgrades versus downgrades, and derive estimates of probability of loan default or stress rates.

Such migration-based measures of credit risk are important inputs in determining lenders' economic capital requirements under the New Basel Accord (Barry, 2001). Compared to the traditional measurement of historic loan default rates, the migration approach provides richer, broader information on the risk stability and quality of a lender's loan portfolio, especially when based on more extensive historical data.

In agricultural lending, a number of lenders, especially Farm Credit System institutions, have begun to use the migration concept to analyze their loan portfolios, although their data histories generally are less than five years in length and updating of the borrower's financial

data is sporadic. As an alternative data generation approach, Barry, Escalante, and Ellinger (2002) have utilized longitudinal farm-level data to produce estimates of transition probability rates, portfolio upgrades and downgrades, and financial stress rates of grain farms in Illinois over a 14-year period. Their study demonstrates the practical relevance of the migration framework in the assessment of portfolio quality and its potential application by farm lenders.

This study pursues a more in-depth analysis of factors that may influence the volatility of migration rates among farm loans. The analysis focuses on demographic factors, farm financial/structural attributes, and macroeconomic conditions expected to influence changes in risk class ratings over time. The first two factor groups represent a choice set of variables which are mostly within the farm manager's control, while the third set represents exogenous conditions beyond the control of individual farmers. The credit migration tendencies of some types of farms could be more vulnerable to these cycles than others (Estrella, 2000). This is corroborated by studies of corporate bond defaults which have established strong linkages between deteriorating economic conditions and transition to default (Helwege and Kleiman, 1997; McDonald and Van de Gucht, 1999; Nickell, Perraudin, and Varotto, 1999). Consistent with the recommendations of the Basel Accord, this study also applies the migration and econometric frameworks to a 10-class credit rating system.

The following sections review the migration concept, discuss the empirical framework, and present the descriptive and econometric results. A summary and conclusions are provided in the final section.

## Measuring Migration

Two important considerations in applying credit migration analysis are (*a*) the choice of classification variable, and (*b*) the type of migration measurement. Options for the classification variable include measures of profitability (return on equity), repayment capacity, and the credit score, which is a composite index that usually includes the former measures and other financial factors.

In this study, a farm's credit score is used to assign farmers to different credit risk classes. The assignments are determined through a credit-scoring model for term loans reported by Splett et al. (1994) that is based on financial ratios recommended by the Farm Financial Standards Council.

Table 1 presents the expanded 10-class rating model, recommended under the Basel Accord to more accurately capture differences in credit classifications of borrowers. The class boundaries are based on the original five-class rating model where, for example, class 1 in the latter model was divided into classes 1 and 2 of the 10-class rating model. Outlier values for the current ratio and the repayment capacity measures are replaced by maximum values used by Barry, Escalante, and Ellinger (2002)—i.e., current ratios exceeding the value of 7 were assigned the maximum value of 7, while the repayment capacity variable bounds are −1.25 and 0.93.

The farm's credit score is evaluated using two measurement approaches:

- A year-to-year transition (1 × 1), which measures movements in credit risk ratings from one year ($n$) to the next ($n + 1$); and

- Three-year average to fourth year transition (3 × 1), which measures credit migration based on a three-year moving average of factor data applied to the fourth year. The 3 × 1 approach, informally acknowledged as preferred by farm lenders, allows more gradual migration than the year-to-year approach.

**Table 1. Credit Scoring, Profitability, and Repayment Classification Intervals**

| Variables (Measures)/Classes | Interval Ranges | Weights |
|---|---|---|
| *LIQUIDITY* (Current Ratio) | | |
| Class 1 | > 2.00 | |
| Class 2 | 1.60–2.00 | |
| Class 3 | 1.25–1.60 | |
| Class 4 | 1.00–1.25 | |
| Class 5 | < 1.00 | ____ × 0.10 = ____ |
| *SOLVENCY* (Equity-Asset Ratio) | | |
| Class 1 | > 0.80 | |
| Class 2 | 0.70–0.80 | |
| Class 3 | 0.60–0.70 | |
| Class 4 | 0.50–0.60 | |
| Class 5 | < 0.50 | ____ × 0.35 = ____ |
| *PROFITABILITY* (Farm Return on Equity) | | |
| Class 1 | > 0.10 | |
| Class 2 | 0.06–0.10 | |
| Class 3 | 0.04–0.06 | |
| Class 4 | 0.01–0.04 | |
| Class 5 | < 0.01 | ____ × 0.10 = ____ |
| *REPAYMENT CAPACITY* (Capital Debt-Repayment Margin Ratio) [a] | | |
| Class 1 | > 0.75 | |
| Class 2 | 0.50–0.75 | |
| Class 3 | 0.25–0.50 | |
| Class 4 | 0.05–0.25 | |
| Class 5 | < 0.05 | ____ × 0.35 = ____ |
| *FINANCIAL EFFICIENCY* (Net Farm Income from Operations Ratio) | | |
| Class 1 | > 0.40 | |
| Class 2 | 0.30–0.40 | |
| Class 3 | 0.20–0.30 | |
| Class 4 | 0.10–0.20 | |
| Class 5 | < 0.10 | ____ × 0.10 = ____ |
| | **= TOTAL SCORE (Numeric)** | _____ |

| Credit Score Classes | | Interval Ranges |
|---|---|---|
| **Five Credit Classes:** | Class 1 | 1.00–1.80 |
| | Class 2 | 1.81–2.70 |
| | Class 3 | 2.71–3.60 |
| | Class 4 | 3.61–4.50 |
| | Class 5 | 4.51–5.00 |
| **Ten Credit Classes:** [b] | Class 1 | 1.00–1.40 |
| | Class 2 | 1.41–1.80 |
| | Class 3 | 1.81–2.25 |
| | Class 4 | 2.26–2.70 |
| | Class 5 | 2.71–3.15 |
| | Class 6 | 3.16–3.60 |
| | Class 7 | 3.61–4.05 |
| | Class 8 | 4.06–4.50 |
| | Class 9 | 4.51–4.75 |
| | Class 10 | 4.76–5.00 |

*Source:* Splett et al. (1994).

[a] New interval ranges for the repayment capacity measure were used in this study since the intervals proposed by Splett et al. (1994) resulted in the heavy concentration of observations in the first class.

[b] The 10 credit classes were derived from the original five credit classes defined by Splett et al. (1994) where class 1 in the latter classification was split into classes 1 and 2 of the new 10-class approach, and so forth.

## Proxy Lender and Macroeconomic Data Sources

In lieu of scarce lender data, this study utilizes information from farm financial records to estimate credit risks. This approach places greater emphasis on quantitative measures of credit risk and does not account for the effects of loan covenants and other risk mitigation strategies employed by lenders. In contrast, farm record data could include borrowers with low credit risk (among non-borrowing farms) and high credit risk (accommodated, for example, under federal financing programs).

The annual farm record data are from farms that maintained certified usable financial records under the Illinois Farm Business Farm Management (FBFM) system during the period 1992 to 2001. The FBFM system has an annual membership of about 7,000 farmers, but rigorous certification procedures implemented by field staff would usually result in much fewer certified farms. In order to apply panel data regression techniques, the data sets include only those farms that consistently maintained certified records over the 10-year period. This more stringent requirement produced a total of 116 farms. The FBFM system provides demographic and structural characteristics of these farms, as well as their farm financial performance.

The inclusion of a risk variable calculated as a three-year moving average and the determination of year-to-year migration rates resulted in eight observations for each farm under the $1 \times 1$ migration approach. The $3 \times 1$ method required four annual data points to calculate a migration rate, yielding seven observations for each farm.

The macroeconomic measures included annual averages of Illinois farm real estate values from the 2001 annual report of the Illinois Agricultural Statistics Service, long-term interest rates on farm loans from the U.S. Department of Agriculture (USDA), annual changes in the S&P 500, and money supply levels reported by the Federal Reserve Bank of St. Louis.

## The Transition Probability Matrices

The average one-period transition matrices for the $1 \times 1$ and $3 \times 1$ measurement approaches are reported in Table 2. The vertical axis corresponds to Period 1 classes while the horizontal axis shows Period 2 classes. Thus, the matrix measures the probability that a farm business will migrate from the row classes to the column classes during each period. This probability is calculated as the ratio of the number of farms that migrate to a certain column class (in Period 2) to the total number of farms originally classified under a particular row class (in Period 1).

The values along the diagonals in Table 2 represent the retention rates, or the probabilities that farms will remain in the same class. The off-diagonal elements represent the percentages of upgrades and downgrades in credit classification. Specifically, rightward movements indicate downgrading while leftward movements indicate upgrading.

The fixed, finite set of 116 farms evaluated during the period 1992–2001 does not accommodate either new entrants into the classification system or farms that terminated operations due to default (i.e., class 5). Financially distressed farms in class 5 could either remain in class 5 or experience an upgrade during the 10-year period.

The migration rates for the five-credit classification system in Table 2 are generally close to values reported by Barry, Escalante, and Ellinger (2002). However, in contrast to the panel data structure of this study, their transition probability matrices were constructed using a longer time frame (1985–1998), and the migration rates were separately calculated using all available farm observations in each pair of subsequent time periods.

**Table 2. Average One-Period Transition Matrices for Credit Scores, Five Credit Classes, 1992–2001 (percent)**

| | Period 2 Classes | | | | |
|---|---|---|---|---|---|
| **Period 1 Classes** | **1** | **2** | **3** | **4** | **5** |
| **A. Year-to-Year Transition (1 × 1):** | | | | | |
| **1** | 73.31 | 18.86 | 7.12 | 0.71 | 0.00 |
| **2** | 18.00 | 43.60 | 26.40 | 10.80 | 1.20 |
| **3** | 7.92 | 25.42 | 42.50 | 15.42 | 8.75 |
| **4** | 4.17 | 19.79 | 31.25 | 28.13 | 16.67 |
| **5** | 1.64 | 9.84 | 27.87 | 21.31 | 39.34 |
| **B. Three-Year Average to 4th Year Transition (3 × 1):** | | | | | |
| **1** | 74.77 | 16.51 | 7.80 | 0.92 | 0.00 |
| **2** | 25.68 | 42.34 | 23.87 | 7.66 | 0.45 |
| **3** | 8.60 | 26.24 | 41.63 | 17.19 | 6.33 |
| **4** | 3.96 | 14.85 | 27.72 | 27.72 | 25.74 |
| **5** | 0.00 | 4.00 | 32.00 | 28.00 | 36.00 |

The year-to-year average retention rates range from 28% to 73%, while the 3 × 1 rates range from 28% to 75%. Consistent with the results of Barry, Escalante, and Ellinger, the retention rates in this study are highest for class 1 borrowers, tend to diminish for the middle-lower credit risk classes, and slightly increase in class 5.

The retention rates under the 10-credit classification system (Table 3) are significantly lower than those based on five credit classes. As before, class 1 farms have greater retention rates compared to farms in other credit classes. Retention rates for class 1 farms were calculated at 65% and 64% for the 1 × 1 and 3 × 1 measurement approaches, respectively. The remainder of the retention rates, however, do not decrease monotonically. In classes 2 to 10, the retention rates range from 13% to 32% under the 1 × 1 approach, and from 12% to 44% under the 3 × 1 approach.

Under a seven-bond rating scale (between the 5- and 10-class rating scales used here), Moody's bond rating retention rates in a one-year transition matrix ranged from 56% to 88% over the period 1983–1998. A similar matrix developed by S&P for 1981–1996 yielded retention rates ranging from 53% to 89%. In contrast, this study reports average retention rates of only 50% and 32% under the 5- and 10-class rating systems, respectively, for the 1 × 1 measurement approach (Table 4).

In general, studies on bond migration reflect a greater downgrading than upgrading of class ratings. For example, Altman and Kao (1992), analyzing first rating changes among bonds, report that 84% of AA bonds downgraded while 17% upgraded. Migration ratings of A bonds, on the other hand, revealed 57% downgrades and 43% upgrades. In the current analysis, this trend only occurs under the 1 × 1 approach, regardless of credit classification system used. Specifically, upgrades and downgrades account for 47% and 53% (23% and 26%, inclusive of class retention rates), respectively, of the total transition to other credit classes using five credit classes (Table 4). The percentages for the 10-class approach are 47% and 54% for upgrades and downgrades, respectively.

The trend is reversed for upgrades and downgrades under the 3 × 1 approach. Perhaps the three-year averaging method used for determining Period 1 classes cushions the impact of volatile and adverse financial conditions on the farm's initial rating.

**Table 3. Average One-Period Transition Matrices for Credit Scores, Ten Credit Classes, 1992–2001 (percent)**

| | Period 2 Classes | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| **Period 1 Classes** | **1** | **2** | **3** | **4** | **5** | **6** | **7** | **8** | **9** | **10** |
| **A. Year-to-Year Transition (1 × 1):** | | | | | | | | | | |
| **1** | 65.03 | 21.47 | 5.52 | 1.84 | 1.23 | 3.68 | 0.61 | 0.61 | 0.00 | 0.00 |
| **2** | 24.00 | 32.00 | 22.40 | 11.20 | 3.20 | 7.20 | 0.00 | 0.00 | 0.00 | 0.00 |
| **3** | 8.26 | 17.36 | 21.49 | 20.66 | 13.22 | 7.44 | 9.92 | 1.65 | 0.00 | 0.00 |
| **4** | 1.64 | 9.84 | 18.03 | 24.59 | 17.21 | 15.57 | 7.38 | 3.28 | 1.64 | 0.82 |
| **5** | 1.52 | 4.55 | 9.09 | 18.94 | 25.76 | 16.67 | 6.82 | 11.36 | 1.52 | 3.79 |
| **6** | 6.48 | 5.56 | 7.41 | 12.96 | 18.52 | 24.07 | 7.41 | 4.63 | 2.78 | 10.19 |
| **7** | 0.00 | 5.45 | 10.91 | 10.91 | 18.18 | 18.18 | 12.73 | 16.36 | 5.45 | 1.82 |
| **8** | 0.00 | 2.33 | 6.98 | 9.30 | 13.95 | 9.30 | 11.63 | 13.95 | 13.95 | 18.60 |
| **9** | 0.00 | 5.56 | 0.00 | 0.00 | 16.67 | 5.56 | 16.67 | 22.22 | 27.78 | 5.56 |
| **10** | 0.00 | 0.00 | 0.00 | 14.63 | 9.76 | 21.95 | 9.76 | 7.32 | 4.88 | 31.71 |
| **B. Three-Year Average to 4th Year Transition (3 × 1):** | | | | | | | | | | |
| **1** | 63.64 | 20.45 | 8.33 | 1.52 | 1.52 | 4.55 | 0.00 | 0.00 | 0.00 | 0.00 |
| **2** | 33.72 | 27.91 | 16.28 | 9.30 | 3.49 | 6.98 | 1.16 | 1.16 | 0.00 | 0.00 |
| **3** | 9.28 | 30.93 | 16.49 | 20.62 | 10.31 | 6.19 | 6.19 | 0.00 | 0.00 | 0.00 |
| **4** | 8.87 | 9.68 | 20.16 | 22.58 | 17.74 | 12.10 | 7.26 | 1.61 | 0.00 | 0.00 |
| **5** | 4.42 | 5.31 | 14.16 | 15.93 | 23.01 | 15.93 | 10.62 | 7.08 | 1.77 | 1.77 |
| **6** | 2.75 | 5.50 | 6.42 | 14.68 | 18.35 | 26.61 | 9.17 | 7.34 | 3.67 | 5.50 |
| **7** | 0.00 | 4.00 | 8.00 | 16.00 | 14.00 | 16.00 | 12.00 | 14.00 | 4.00 | 12.00 |
| **8** | 0.00 | 3.92 | 0.00 | 5.88 | 11.76 | 13.73 | 9.80 | 21.57 | 19.61 | 13.73 |
| **9** | 0.00 | 0.00 | 0.00 | 4.00 | 20.00 | 12.00 | 20.00 | 24.00 | 12.00 | 8.00 |
| **10** | 0.00 | 0.00 | 0.00 | 4.00 | 16.00 | 16.00 | 4.00 | 8.00 | 8.00 | 44.00 |

**Table 4. Summary Transition Rates for Illinois Farms, 1992–2001 (percent)**

| | Summary Rates | |
|---|---|---|
| **Migration Trends and Measurement Approaches** | **5 Credit Classes** | **10 Credit Classes** |
| **Retention:** [a] | | |
| Year-to-Year Transition | 50.43 | 31.57 |
| Three-Year Average to 4th Year Transition | 48.65 | 29.31 |
| **Upgrades:** [b] | | |
| Year-to-Year Transition | 23.17 | 31.79 |
| Three-Year Average to 4th Year Transition | 26.23 | 36.82 |
| **Downgrades:** [c] | | |
| Year-to-Year Transition | 26.40 | 36.64 |
| Three-Year Average to 4th Year Transition | 25.12 | 33.87 |

[a] Summary retention rates were calculated as the average of all diagonal elements of the migration matrices.

[b] Summary upgrade rates were calculated as the average of all transition rates below the diagonal elements of the migration matrices.

[c] Summary downgrade rates were calculated as the average of all transition rates above the diagonal elements of the migration matrices.

## Econometric Framework

The empirical framework utilizes ordered and time-series cross-sectional logit regression techniques performed using version 7.0 (special edition) of Stata software (Stata Corporation, 2002). Four versions of the estimating model are developed using the two measurement approaches (i.e., annual and $3 \times 1$ migrations) for the 5- and 10-credit classification systems.

Diagnostic test results indicate the need to formulate two separate models for the annual and $3 \times 1$ migration data sets. The Breusch-Pagan Lagrangian multiplier (BPLM) test for random effects (with a null hypothesis that the variance of the unit-specific residual is zero) yielded contrasting results for these two data sets. Annual migration data sets for the 5- and 10-credit classifications yielded significant BPLM $\chi^2$ statistics, thus violating the necessary random-effects assumption. Insignificant Hausman test results further suggest the relevance of an ordinary ordered logit regression technique for these data sets. In contrast, BPLM and Hausman test results support the random-effects model for both the 5- and 10-credit classification data sets using the $3 \times 1$ method.

The conceptual form of the estimating equations is:

$$(1) \quad Y_{it}^{*} = \alpha + \mathbf{V}_{it}'\beta_1 + \mathbf{W}_{it}'\beta_2 + \mu_i + \varepsilon_{it},$$

where $Y_{it}^{*}$ is an ordered, discrete migration variable, evaluated on every pair of subsequent periods, that has values of 2 for upgrades, 1 for retentions, and 0 for downgrades; $\alpha$ is the intercept; the vectors $\mathbf{V}_{it}$ and $\mathbf{W}_{it}$ (with their corresponding vectors of regression coefficients $\beta_1$ and $\beta_2$, respectively) represent structural/demographic and macroeconomic factors that could influence class migrations; and $\mu_i$ and $\varepsilon_{it}$ are the model's error terms, with the latter representing the stochastic unit-specific error components.

Under the random-effects framework, the error terms are assumed to demonstrate the following properties (Greene, 1993):

$$E\{\mu_i\} = 0 \text{ and } Var\{\mu_i\} = \sigma_\mu^2,$$

$$Cov\{\varepsilon_{it}, \mu_i\} = 0,$$

$$Var\{\varepsilon_{it} + \mu_i\} = \sigma_\varepsilon^2 + \sigma_\mu^2 = \sigma^2,$$

$$Corr\{\varepsilon_{it} + \mu_i, \varepsilon_{is} + \mu_i\} = \rho.$$

Logistic regression applies maximum-likelihood estimation after transforming the dependent variable into a logit variable, defined as the natural log of the odds that the event of interest will or will not occur. The ordered logit model is "built around a latent regression in the same manner as the binomial probit model" (Greene, 1993, p. 672). Thus, the cumulative normal probability for a credit upgrade ($Y_{it}^{*} = 2$) is specified as a nonlinear (logit) function of demographic and structural attributes of the farm business ($\mathbf{V}_{it}$) and prevailing macroeconomic conditions ($\mathbf{W}_{it}$). Moreover, the observed migration rate denoted by $Y_{it}^{*}$ in equation (1) depends on a continuous latent variable ($Y_{it}$) having various threshold points, as follows:

$$(2) \quad Y_{it}^{*} = 0 \text{ if } Y_{it} \le \delta_1,$$

$$Y_{it}^{*} = 1 \text{ if } \delta_1 \le Y_{it} \le \delta_2,$$

$$Y_{it}^{*} = 2 \text{ if } Y_{it} \ge \delta_2,$$

where $\delta_1$ and $\delta_2$ are unknown parameters that collectively define the range of values for the latent variable (Greene, 1993). The $\delta$'s are estimated, along with the unknown $\beta$ coefficients of the explanatory variables.

Assuming that $\varepsilon_{it}$ in equation (1) is standard normally distributed across observations, the probabilities of $Y_{it}^{*}$ taking values of 0, 1, and 2 are:

$$(3) \quad P(Y = 0) = \frac{1}{1 + \exp\left(\left(\sum_{k=1}^{K} \beta_k X_k\right) - \delta_1\right)},$$

(continued ...)

$$P(Y=1) = \frac{1}{1+\exp\left(\left(\sum_{k=1}^{K}\beta_k X_k\right)-\delta_2\right)} - \frac{1}{1+\exp\left(\left(\sum_{k=1}^{K}\beta_k X_k\right)-\delta_1\right)},$$

$$P(Y=2) = \frac{1}{1+\exp\left(\left(\sum_{k=1}^{K}\beta_k X_k\right)-\delta_2\right)},$$

where $X_k$ contains regressors $\mathbf{V}_{it}$ and $\mathbf{W}_{it}$, and $\beta_k$ contains their corresponding coefficients $\beta_1$ and $\beta_2$, respectively.

## Demographic and Structural/ Financial Factors

This analysis considers how farm size, farmland control arrangements, enterprise diversification strategies, and productivity of the existing farm asset complement may influence credit migration. Farm size (*SIZE*), measured by gross revenues, could influence the probability of upward migration if larger farms experience greater production efficiencies and economies of scale. These benefits, however, could be tempered by higher leverage which creates greater financial stress.

The contrasting risk-return tradeoffs and liquidity mechanisms, offered by ownership through debt financing, share leasing, and cash leasing, emphasize the importance of the *TENURE* variable, which is defined as the ratio of owned to total tillable acres of farmland. Ellinger and Barry (1987) have confirmed that higher tenure ratios are usually associated with lower accounting rates of return. Share leasing, on the other hand, offers a highly risk-efficient financing option for farmers (Barry et al., 2000). The positive correlation between the value of harvested crops and the tenant's rental obligation to the landowner stabilizes net income, resulting in greater risk-reducing benefits for the farm operator. Thus, decisions on farmland control arrangements could significantly affect the farm's credit migration.

Reductions in risk from enterprise diversification could also influence the probability of upward credit migration. An enterprise diversification index (*DIVER*) is constructed for each farm using the Herfindahl measure of concentration, calculated as:

$$H = \sum_{i=1}^{n} (Share_i)^2.$$

The index is based on the allocation of gross farm revenues among the sale of crops, livestock, and auxiliary farm services/products. A fully specialized farm has an index value of 1, while smaller index values indicate more diversified business portfolios. The influence of diversification on the dependent variable will depend on tradeoffs between risk reduction and high revenue potentials from specialization (Barry, Escalante, and Bard, 2001).

The farm's asset acquisition decisions are reflected by the asset turnover ratio (*ATO*), calculated by dividing gross farm revenues by total farm assets. This measure reflects the capability of the farm's existing asset complement to generate revenues. The goal is to maximize the assets' productive capacity in order to produce optimal levels of output and sales.

In addition to these structural factors, demographic variables pertaining to the farm operator's age (*AGE*), geographical location (*URBINF*), and the soil's productivity rating (*SOIL*) are also included in the models. Previous empirical studies contend that older farmers tend to be more risk averse (Patrick, Whitaker, and Blake, 1980; Lins, Gabriel, and Sonka, 1981), and thus implement more cautious business plans.

Opportunities for improvements in credit risk could be greater for farms located near large urban areas. These benefits might include minimization of transaction costs and greater chances at obtaining premium production contracts. In this study, the location factor is represented by *URBINF*,

an urban influence dummy variable based on a USDA index where counties are classified into nine mutually exclusive groups according to the adjacency to metro areas. This analysis simplifies the index into a binary dummy variable equal to 1 for counties within metropolitan areas (both large areas with 1 million or more residents and small areas with less than 1 million residents) as well as for counties adjacent to large metro areas that either contain or do not contain all or part of its own city of 10,000 or more residents (USDA's codes 1–4). The variable takes a value of 0 for non-metropolitan counties that are either adjacent to smaller metropolitan areas or are totally rural and isolated communities (USDA's codes 5–9).

The farm's soil productivity rating (*SOIL*), is an average index representing the inherent productivity of all tillable land on a farm. It reflects the influence on credit migration of the income-generating capacity of crop operations. More stable and higher yield levels are generally associated with more productive soil, and thus would positively affect economic performance.

An income risk (*INCRISK*) component, measured as the coefficient of variation (CV) of net farm income, is introduced in the model. Greater stability of returns from farm revenue sources enables farmers to devise effective business plans that anticipate adjustments in the farm's liquidity and profitability conditions. Ultimately, better farm financial performance results in greater likelihood of improvements in credit risk ratings.

## Macroeconomic Variables

The success or failure of a farm business does not solely depend on the farm's ability to implement growth-enhancing and risk-reducing business plans. Macroeconomic forces, beyond the farmer's control, could significantly influence the effectiveness of such business strategies. This analysis considers several macroeconomic measures related to economic growth, lending conditions, investor expectations, and price level changes that are expected to influence the credit risk migration trends of farm businesses.

Among alternative proxy measures for economic growth activity, the annual growth rates of farm real estate values (*FLGRWTH*) provide a comprehensive indication of growth both within the farm industry and the economy in general. Variation in the growth of farm real estate prices does not only depend on farm-related conditions such as changing government farm policies, production risks, and farm credit conditions, but also on non-farm investment opportunities dictated by the economy's demands for commercial, residential, and recreational facilities, among others.

The availability and cost of credit are also important determinants of the likelihood of upward migration. The annual growth rate of the economy's monetary stock (*MNYGRWTH*) is used in this analysis to reflect changes in credit availability conditions. Bankruptcy studies have observed that the majority of business failures among small firms occur during tight money conditions when lenders usually resort to small business "credit-rationing" to protect their loan portfolios (Altman, 2001).

Changes in credit costs are represented by the annual change in interest rates for agricultural mortgage (long-term) loans (*AGRATES*). Interest rate adjustment is normally among the policy options used by the Federal Open Market Committee to achieve certain economic goals. For instance, the Federal Reserve Board's aggressive rate-cutting campaign from January 2001 to June 2003 was designed to stimulate greater economic activity from the business, consumer, and market sectors of the economy. Compared to short-term interest rates that are easily affected by changes in the federal funds rate, longer-term borrowing rates follow a more complicated adjustment process involving other indicators, such as speculative and precautionary factors.

**Table 5. Results of Ordered and Random Effects Logit Regression, Multinomial Dependent Variable**

| | Year-to-Year Transition Ordered Logit Model | | | |
|---|---|---|---|---|
| | 5 Credit Classes | | 10 Credit Classes | |
| **Variables** | **Coefficient** | **Z-Statistic** | **Coefficient** | **Z-Statistic** |
| **A. Demographic & Financial/Structural Variables:** | | | | |
| *SIZE* (farm size, $) | -4.07e-07 | -0.83 | -3.28e-07 | -0.69 |
| *TENURE* (tenure ratio) | 0.38878 | 1.12 | 0.23147 | 0.68 |
| *DIVER* (diversification index) | -0.18796 | -0.52 | 0.16065 | 0.45 |
| *ATO* (asset turnover) | 0.70899* | 1.76 | 0.69452* | 1.73 |
| *AGE* (operator's age, years) | 0.01033 | 1.44 | 0.01183* | 1.69 |
| *URBINF* (urban influence dummy) | 0.05271 | 0.36 | -0.01525 | -0.10 |
| *SOIL* (soil productivity rating) | -0.00267 | -0.39 | -0.00525 | -0.77 |
| *INCRISK* (income risk) | 0.00467 | 0.76 | 0.00329 | 0.57 |
| **B. Macroeconomic Variables:** | | | | |
| *FLGRWTH* (farmland value growth, %) | 16.09892*** | 3.46 | 16.74890*** | 3.63 |
| *MNYGRWTH* (money supply growth, %) | 13.20888*** | 3.86 | 16.98151*** | 4.99 |
| *SPCHG* (S&P 500 change, %) | 4.71589** | 2.40 | 6.42119*** | 3.26 |
| *AGRATES* (change in ag LT interest rates, %) | -1.04519 | -0.21 | 2.76379 | 0.57 |
| Log Likelihood | -934.70767 | | -982.63276 | |
| LR $\chi^2$ Statistic | 52.73*** | | 69.26*** | |

*Note:* Single, double, and triple asterisks (*) denote significance at the 90%, 95%, and 99% levels, respectively.

Finally, credit risk migration could also be affected by the general economic outlook as reflected in both the prices being paid for holding financial assets, such as stocks, and the risk premium investors are willing to pay for keeping riskier financial assets (Altman, 2001). The S&P 500 index of stock prices is used as a proxy for the overall stock market performance. Annual changes in the stock price index (*SPCHG*) reflect changes in the investors' demand for holding stocks.

## Econometric Results

Except for the income risk variable, the dependent variable is regressed against the two-year and four-year averages of the annual values of the structural and demographic variables under the annual and 3 × 1 migration frameworks, respectively. One-year lagged growth rate measures for the macroeconomic variables are used for the annual migration data sets. In the 3 × 1 migration data sets, the equivalent growth rate measures the average growth rate for every four-year period.

The models' coefficients provide unambiguous indications of changes in the probability of moving from the lowest to the next highest categories, and vice versa (upgrades and downgrades), in addition to important information on the model's explanatory power and the statistical significance of each individual independent variable. The regressors' directional effects can be discerned, however, from estimates of their marginal effects. The following sections discuss the significance of certain variables and their directional effects in each category of the dependent variable.

### Significant Determinants

Table 5 reports the coefficient estimates and the resulting *Z*-statistics for the significance tests for the four versions of the model. A positive (negative) coefficient for a regressor suggests it increases (decreases) the odds of a credit class upgrade.

**Table 5. Extended**

| | Three-Year Average to 4th Year Transition Random-Effects Model | | | |
|---|---|---|---|---|
| | 5 Credit Classes | | 10 Credit Classes | |
| **Variables** | **Coefficient** | **Z-Statistic** | **Coefficient** | **Z-Statistic** |
| **A. Demographic & Financial/Structural Variables:** | | | | |
| *SIZE* (farm size, $) | -7.04e-07 | -1.04 | -7.65e-07 | -1.28 |
| *TENURE* (tenure ratio) | 0.43593 | 0.85 | 0.05002 | 0.11 |
| *DIVER* (diversification index) | 0.01403 | 0.03 | -0.75683* | -1.63 |
| *ATO* (asset turnover) | -0.17121 | -0.30 | 0.17256 | 0.33 |
| *AGE* (operator's age, years) | 0.00796 | 0.76 | 0.01058 | 1.16 |
| *URBINF* (urban influence dummy) | 0.16489 | 0.77 | 0.18497 | 1.00 |
| *SOIL* (soil productivity rating) | 0.00751 | 0.75 | -0.01256 | -1.43 |
| *INCRISK* (income risk) | 0.00306 | 0.31 | 0.00654 | 0.68 |
| **B. Macroeconomic Variables:** | | | | |
| *FLGRWTH* (farmland value growth, %) | 148.18790*** | 5.25 | 157.92610*** | 6.21 |
| *MNYGRWTH* (money supply growth, %) | 11.41453** | 2.10 | 14.99409*** | 3.01 |
| *SPCHG* (S&P 500 change, %) | 3.24643* | 1.66 | 4.72747*** | 2.70 |
| *AGRATES* (change in ag LT interest rates, %) | -17.09374*** | -2.85 | -19.33260*** | -3.53 |
| Log Likelihood | -434.27992 | | -490.38277 | |
| Wald $\chi^2$ Statistic | 40.23*** | | 54.11*** | |

Among the two groups of regressors, none of the eight demographic, financial/structural variables had a significant influence on the probability of credit migration in the 3×1 random effects model using five credit classes. This result could reflect the distributional characteristics of the data set—i.e., homogeneous demographic and structural attributes may not yield enough variability to significantly affect credit migration probabilities. Moreover, certain variables could have dual, offsetting effects on the dependent variable. For example, the greater production capacity of larger farms could favor upgrades, while shortfalls in production efficiency could lead to downgrades.

The other three models (ordered logit models for 5-class and 10-class annual migration and 3×1 random effects model using 10 credit classes) produced at most two significant demographic, structural/financial variables. The diversification (*DIVER*) variable's significant negative coefficient in the 3×1 method, 10 classes model suggests that increasing specialization of farm enterprises could lead to greater probability of class downgrades. This result aptly describes the regional distribution of farm operations in Illinois where the relatively less productive soil profiles of the southern counties create a greater necessity to diversify farm enterprises. In contrast, the highly productive soils in the north and central regions normally allow their farms to specialize in corn, soybean, and wheat production. However, this study's sample period captures episodes of steadily declining grain prices as a result of supply overstock in the mid-1990s while federal programs wavered from providing risk-reducing countercyclical subsidies to fixed, decoupled payments. Hence, the more diversified crop-livestock farms in less productive regions have been more resilient and more likely to realize upward mobility in credit risk ratings.

Asset turnover (*ATO*) is significant and positive in both the 5-class and 10-class data sets, suggesting that farms better able to increase the productive capacity of their farm asset complements are more likely to experience rating upgrades.

**Table 6. Marginal Effects of Significant Explanatory Variables**

| | 5 Credit Classes | | |
|---|---|---|---|
| **Significant Variables** | **Downgrades** | **Retention** | **Upgrades** |
| **A. Year-to-Year (annual) Transition:** | | | |
| *ATO* (asset turnover) | -0.13446 | 0.01192 | 0.12254 |
| *AGE* (operator's age, years) | — | — | — |
| *FLGRWTH* (farmland value growth, %) | -3.05305 | 0.27064 | 2.78242 |
| *MNYGRWTH* (money supply growth, %) | -2.50498 | 0.22205 | 2.28293 |
| *SPCHG* (S&P 500 change, %) | -0.89434 | 0.07928 | 0.81506 |
| **B. Three-Year Average to 4th Year Transition (3×1):** | | | |
| *DIVER* (diversification index) | — | — | — |
| *FLGRWTH* (farmland value growth, %) | -26.94238 | -1.23399 | 28.17636 |
| *MNYGRWTH* (money supply growth, %) | -2.64853 | -0.12130 | 2.76983 |
| *SPCHG* (S&P 500 change, %) | -0.77385 | -0.03544 | 0.80929 |
| *AGRATES* (change in ag LT interest rates, %) | 4.40746 | 0.20187 | -4.60932 |

*AGE* also has the same effect in the 10-class data set using the annual migration method. Its positive coefficient suggests older, more experienced farmers are more likely to experience rating upgrades. Moreover, older farmers are more likely to maintain favorable, affordable debt loads that have been gradually retired over the years.

The overall weak, insignificant impact of the farm's structural and demographic profile could imply that such attributes are emphasized more for making loan decisions and defining loan covenants. Once the loan is granted and serviced, these factors become less relevant in determining credit migrations.

A major result of this analysis is the strong influence of macroeconomic variables on the dependent variable. Changes in the values of money supply (*MNYGRWTH*), farm real estate (*FLGRWTH*), and stock index (*SPCHG*) are consistently significant among the macroeconomic variables in all four estimating equations. High growth rates in money supply (*MNYGRWTH*) relax the credit availability constraint and allow farmers to undertake strategies that increase the likelihood of credit upgrades. *FLGRWTH* has a similar positive effect on the dependent variable. Increases in farm real estate values point to a flourishing farm economy, thereby increasing the probability of credit upgrades. The positive sign of *SPCHG* is consistent with the expectation that a growing stock market index could influence the probability of upgrades.

*AGRATES*, a measure of the changes in agricultural mortgage rates, is significant and negatively signed in both model versions using the 3×1 measurement approach. Higher interest rates can increase financial risks for indebted farmers and lead to downgrades in risk ratings.

## Directional Effects

The directional effects are more explicitly given by the marginal effects of the significant variables in Table 6 (Stata Corporation, 2002). Among the demographic and structural variables, the probability of experiencing a downgrade is more sensitive to unit changes in asset turnover (*ATO*) than to similar increments in operator's age (*AGE*). Specifically, the likelihood of a downgrade decreases by a range of 0.13446 to 0.16002 due to a unit increase in *ATO*, while the equivalent change for *AGE* is 0.00272. The probabilities of retentions and upgrades increase for every unit change in each of these two financial variables, with *ATO* yielding the larger effects.

**Table 6. Extended**

| Significant Variables | 10 Credit Classes | | |
|---|---|---|---|
| | Downgrades | Retention | Upgrades |
| **A. Year-to-Year (annual) Transition:** | | | |
| *ATO* (asset turnover) | -0.16002 | 0.01248 | 0.14754 |
| *AGE* (operator's age, years) | -0.00272 | 0.00021 | 0.00251 |
| *FLGRWTH* (farmland value growth, %) | -3.85894 | 0.30092 | 3.55801 |
| *MNYGRWTH* (money supply growth, %) | -3.91253 | 0.30510 | 3.60743 |
| *SPCHG* (S&P 500 change, %) | -1.47944 | 0.11537 | 1.36407 |
| **B. Three-Year Average to 4th Year Transition (3×1):** | | | |
| *DIVER* (diversification index) | 0.25208 | 0.01141 | -0.26348 |
| *FLGRWTH* (farmland value growth, %) | -31.52756 | -1.42648 | 32.95404 |
| *MNYGRWTH* (money supply growth, %) | -3.15944 | -0.14295 | 3.30239 |
| *SPCHG* (S&P 500 change, %) | -0.92407 | -0.04181 | 0.96588 |
| *AGRATES* (change in ag LT interest rates, %) | 4.19605 | 0.18985 | -4.38590 |

The positively signed macroeconomic variables (*SPCHG*, *MNYGRWTH*, and *FLGRWTH*) in Table 5 consistently have marginal effects revealing a negative and a positive effect on the probability of a class downgrade and upgrade, respectively, in Table 6. Their directional effects on the retention probability, however, are not homogeneous. These variables had negative effects on the retention probability in the two models under the 3×1 method. The equivalent effect in the annual migration models is positive.

*AGRATES*, a negatively signed regressor in Table 5, has positive marginal effects on downgrade and retention probabilities, while its marginal effect on the probability of upgrades is negative. Among all the macroeconomic variables, farm real estate growth yielded the strongest marginal effects. This variable consistently negatively influences downgrade probabilities. Notably, in the 3×1 models, this effect ranges from 26.9 to 31.5 times. In the same models, this variable's effect on upgrade probabilities is positive and ranges from 28.2 to 33.0 times. The results for retention probabilities are mixed, with positive probability effects in the annual models and negative effects in the 3×1 models. The variable's effect, however, is consistently positive for the probability of a class upgrade.

## Summary and Conclusions

This study introduces two new perspectives in understanding the application of the migration model to farm credit risk analysis, i.e., the expansion of the credit classification system from 5 to 10 classes and possible determinants of credit migration probabilities. Consistent with the recommendation of the Basel Accord, an expanded 10-class version of the 5-class credit rating system is introduced to determine its impact on transition probabilities. The econometric analysis also considers farm-level as well as macro factors that are both within and beyond the farm manager's control.

The migration matrices obtained in this study reflect trends of lower class retention rates and highly volatile transition probabilities compared to results obtained for bonds and other publicly traded securities (Barry, Escalante, and Ellinger, 2002; Altman and Kao, 1992), although the lenders' subjective inputs in the loan decision process have not been considered here. Nonetheless, this result is consistent with the riskier nature of farming operations that are easily more susceptible to seasonal fluctuations in weather and market conditions than firms belonging to other industries. Notably, the shift from the conventional 5-credit classification system to an expanded 10-class approach

produced a greater incidence of class migrations with higher overall rates of upgrades and downgrades than retention rates.

The econometric results under the 5- and 10-credit rating scales were, however, more consistent with each other. In general, this analysis demonstrates that most farm-specific factors do not have adequate explanatory influence on the probability of credit risk transition. The homogeneity of farm conditions or the offsetting interaction effects of certain factors could have minimized the importance of the farms' demographic and structural attributes.

The more compelling result is the dominance of macroeconomic factors on the probability of credit migration. Increases in stock price indexes and farm real estate values both signal a growing economy through aggressive investment activities and expansive project developments. They are thus associated with the greater likelihood of class upgrades. The relaxation of the credit constraint through increments in the money supply level strengthens the likelihood of upgrades, while increases in interest rates make downgrades more likely.

Future research applying the migration framework to farm finance could expand the analytical model used here to account for other factors directly or indirectly affecting transition probability rates such as weather, irrigation systems, technological change, and social capital.

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# Factors Affecting Farm Enterprise Diversification

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## Abstract

Enterprise diversification is a self-insuring strategy used by farmers to protect against risk. This study examines the impact of various farm, operator, and household characteristics on the level of onfarm enterprise diversification. Evidence exists that larger farms are more specialized. Also, farmers who participate in off-farm work, farms located near urban areas, or farms with higher debt-to-asset ratios are less likely to be diversified. In contrast, evidence suggests there is a significant positive relationship between diversification and whether the farm business has crop insurance, is organized as a sole proprietorship, or receives any direct payments from current farm commodity programs.

*Key words:* debt-to-asset ratio, enterprise diversification, farm size, government payments, insurance, location, off-farm income, soil productivity

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Historically, enterprise diversification has been an important characteristic of American agriculture. Diversification was a requirement for subsistence farms or even commercial farms with limited access to transportation or that were geographically isolated. In recent decades, the trend has been toward specialization enabling farmers to concentrate their management skills, capital resources, and specialized knowledge on the production of a small number of commodities. Specialization allows farmers to pursue the production of those commodities for which they have the greatest relative advantage or the least relative disadvantage given the physical and biological factors and economic forces that limit their enterprise possibilities (Castle, Becker, and Nelson, 1987). Nonetheless, as Montgomery (1994) points out, the diversified (multi-product) firm still is the rule rather than the exception.

Farming is a risky business. However, enterprise diversification is a risk management strategy an individual farmer can use to reduce the adverse impact of wide fluctuations in yields and/or prices of specific commodities, whether due to natural causes such as weather or the impact of uncertainties derived from business cycles, wars, or other factors. Besides its risk-reduction benefits, diversification provides an opportunity to exploit the potential complementary and/or supplementary relationships between enterprises through improved utilization of the natural resources of the farm and available operator and family labor and management skills over the entire year. In addition, enterprise diversification may be advantageous when local demand exists for specific products

(niche or specialized market opportunities) that are not competitive with the primary enterprise(s) and yet earn a profit.

Farming deals with uncertain factors such as weather and market conditions. These uncertainties can result in variable returns (farm income) to the decisions farmers make in a particular year. Therefore, farm income variability is a problem the farm household must deal with. Enterprise diversification is one method of reducing income variability (Robison and Barry, 1987; Newbery and Stiglitz, 1985). Diversification is characterized by two distinct aspects. One is that of planning under an assumption of perfect knowledge, and the other is to minimize the variance of an outcome by attempting to put a floor under the income level or by preventing the occurrence of undesirable outcomes (Heady, 1952). Farmers and farm managers, faced by price and yield variability, may wish to select a combination of enterprises to reduce the variability of farm income.

Diversification, as a frequently used risk management strategy, has the added advantage of mitigating price risk as well as variations in outputs since it reduces reliance on only one market and exposure to its price fluctuations (Clark, 2004). In less developed economies, Walker and Jodha (1986) report multiple crops and inter-cropping are common, including agro-forestry. In the United States, corn and soybeans, and corn with beef or hogs are common enterprise combinations, but economically sized and diversified enterprises may not be realized on the average farm. Livestock investments should be large enough to take advantage of the economies of size, but divisible into units that can be financed by the average farm business. The management skills and capital required to establish and successfully maintain such a business may be beyond the ability of some farmers.

Despite the frequent observation that diversification plays an important role in agriculture, there are only a few empirical studies addressing the factors found to contribute to farm enterprise diversification. One purpose of this study is to examine factors associated with farm enterprise diversification in the United States in 1996 and 2000. This focus is particularly important, as it allows for testing the notion that production flexibility prescribed under the Federal Agriculture Improvement and Reform (FAIR) Act of 1996 would allow farmers to alter their cropping mix (or production decisions). If this is the case, then one would expect the impact of government payments[1] on diversification in 1996, when FAIR was enacted, to differ from the impact in 2000 after several years had passed to allow time for farmers to adjust their production decisions. The analysis is conducted on a national scope using farm-level data with the unique feature of a larger sample than previously reported, comprising farms of different economic sizes and in different regions of the United States.

The dual objectives of this study are: (*a*) to determine whether the FAIR Act of 1996 had a discernible impact on the level of enterprise diversification between 1996 and 2000 on sample farms, i.e., did the production flexibility provisions of the 1996 legislation influence the long-term trend toward greater specialization on U.S. farms? and (*b*) to identify those farm business, operator, and farm household characteristics associated with onfarm enterprise diversification.

## Literature Review

Analysis of the factors affecting farm diversification remains an active area of research in strategic management and industrial organization (Briglauer, 2000). While the literature on onfarm diversification in the United States is limited, researchers in European countries

[1] The government payments considered in this analysis include Agricultural Market Transition Act (AMTA) payments that are based on historical production and yield levels, and loan deficiency payments (LDP).

such as England, France, and Greece have studied onfarm diversification for some time. Ilbery (1991) suggests business diversification can be viewed as the outcome of a range of factors working both "externally" and "internally" on the farm household. Internal factors include farm and farm household characteristics that help to determine the nature of diversification, if any, undertaken by the farm business.

A common finding in the literature on onfarm diversification is the correlation between farm size and diversification. Findings by some researchers indicate large farms are more likely to be diversified (Ilbery, 1991; Pope and Prescott, 1980; Shucksmith and Smith, 1991) because they can exploit capital more effectively and more efficiently employ available labor. However, White and Irwin (1972), using aggregate U.S. Census data to compare diversification across farm size classes, concluded that larger farms are more specialized based on the perceived benefits from economies of scale. In analyzing data on 2,192 farms across three U.S. regions, Sun, Jinkins, and El-Osta (1995) distinguished between different "stages of diversification" which were found to influence the relationship between size and diversification.

Soil productivity should have implications for onfarm enterprise diversification. One notion is that if the soils are productive, the farm operator will have more cropping pattern options available, and therefore be more inclined to engage in more than one crop enterprise on the farm. However, if the farm includes soils of differing characteristics and productivities, the farm operation will more likely include livestock or specialty crop enterprises that are better suited to effective utilization of the farm's soil resource endowment. In addition, crop diversification in the form of diversified crop rotations has been shown to contribute to higher and more stable net farm income when compared to traditional monoculture which, over extended periods of time, has shown evidence of degradation of soil quality and reduced crop productivity (Clark, 2004; Zentner et al., 2002). Consequently, this study includes a measure of soil productivity in the analytical model.[2]

The proximity of a farm to an urban area will be less likely to encourage diversification.[3] One argument in support of this assertion is that a farm operator located near an urban area, when faced with financial stress, is more likely to sell the farm and move out of agriculture, or to seek off-farm employment rather than engage in onfarm enterprise diversification.[4] This notion is consistent with the land pricing literature (Moss and Schmitz, 2003).

Farmers may adopt diversification strategies as a way to reduce the financial risks inherent in their farm business. Barry and Baker (1984) explain that financial risk increases with higher levels of leverage. Hence, one might expect a positive association between leverage and onfarm enterprise diversification.

In a study of California farmers, Pope and Prescott (1980) used net worth per acre cropped as a measure of financial risk. They found that farms with higher net worth are more specialized, and farm organization has an impact on onfarm diversification. Corporate farms were found to be more specialized than other farms. Further, the authors note that

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[2] A soil productivity index, ranging from 0–100, is used—with zero representing the least productive soil and 100 representing the most productive soil (for further details, see Pierce et al., 1983).

[3] An urban influence index (*FRM_URBAN*) was derived from a gravity model of urban development by Economic Research Service (ERS) geographers and economists. A gravity index accounts for both population size and distance of the parcel from that population. The index, which has been labeled as a population-accessibility index, increases as population increases and/or as distance from the parcel to population decreases. The population-accessibility index is calculated on the basis of population within a 50-mile radius of each parcel (for more details, see Moss and Schmitz, 2003, Chapter 18).

[4] Off-farm employment is a form of income diversification for the farm household. However, this analysis is confined to examining onfarm enterprise diversification.

increased farm diversification places greater demands on management and coordination skills. Improved managerial skills, education, and training better prepare the farm operator to run a farm which is more diversified. Another factor identified as critical in onfarm diversification is age of the operator. Because farmers tend to accumulate wealth over a lifetime, one would expect older farm operators to be less likely to engage in onfarm diversification since age and wealth are positively correlated. Based on this relationship, Pope and Prescott argue that wealthier farmers are less risk averse and hence less diversified, all else being equal.

Family size is an indicator of onfarm labor availability and an attribute that affects farm diversification. As Bowler et al. (1996) note, larger families may have pressure to create employment opportunities on the farm, and consequently encourage the operator to adopt a land use pattern that utilizes available resources more effectively, including family labor, in an effort to increase profit. Time allocation of operator and family labor between farm and off-farm alternatives influences onfarm enterprise diversification. If operators are working full time on the farm, this may be an indicator that the comparative advantage for their labor is on the farm. Hence, operators would be more likely to diversify onfarm enterprises to increase profit. Full-time farming status may also be an indicator of farm-specific human capital.

Farmers use various private risk management strategies (such as production and marketing contracts, insurance, and input contracts) to reduce financial risk and variability in production (Harwood et al., 1999). There is a view that farmers who use crop insurance or business insurance[5] and contracts are less likely to pursue onfarm diversification—the contention being that onfarm diversification and private risk management strategies are complements. However, a risk-averse farmer who uses onfarm diversification may also buy insurance and use production and marketing contracts to reduce agricultural production risks.

Robison and Barry (1987) suggest that the availability of government payments is one of the factors affecting onfarm diversification. Farm operators and their spouses work off the farm to increase their total household income and also to reduce the variability in household income associated with fluctuations in farm income (Mishra and Goodwin, 1997). If the household receives income from off-farm work, operators of those farms are less likely to pursue onfarm diversification as a method of reducing financial risk associated with farming.

The farm's location among the geographic regions may be thought of as a physical characteristic of the farm (Damianos and Skuras, 1996). However, location places constraints (climatic, soil characteristics, topographic, etc.) on potential farm business strategies and imposes limitations on human capital development opportunities. In addition, location influences the choice of enterprise options on the farm and the development of alternative methods of marketing the agricultural products.

Although the preceding studies differ substantially in their empirical approaches and results reported, they share two common characteristics. First, they consider farm production diversification only and do not control for the impact of additional off-farm income.[6] Second, the impact of commodity program participation is generally ignored. To the extent that participation in government commodity programs is viewed as a risk-reducing mechanism (Goodwin, 1993; Calvin, 1992; Just and Calvin, 1990), and

[5] The farm business insurance category includes all casualty, hail, and blanket insurance policies.

[6] Mishra and Goodwin (1997) examined income diversification only from the time allocation perspective.

because the 1996 FAIR Act implements a reduction in commodity program payments,[7] this study specifically examines the potential impact of commodity program payments (AMTA and LDP) on diversification. The need for this focus lies in the effect a change in commodity specialization or diversification might have on input usage and/or the environment.

## Theoretical Consideration

The mean-variance (E-V) approach, which underlies this study, is a straightforward extension of utility theory. Under the assumptions of an E-V approach, an individual's preference ordering depends solely on the mean and variance of returns—an uncertain prospect can be represented fully by its mean and variance. The decision rule used by a farmer to choose the appropriate enterprise mix from among virtually unlimited possibilities is to maximize the utility of income derived from the possible enterprise portfolios, where utility depends only on the mean and variance of returns. The assumption here is that the farmer's preference function can be described, approximately at least, in terms of the mean and the variance of returns.

There are several reasons why this assumption may be valid. One is that individuals maximize expected utility, and either the underlying utility function is approximately quadratic in income or the distribution of returns involves only the mean and variance. Second, even if expected utility maximization is not assumed, the mean-variance approach still can be considered a reasonable first approximation of behavior.[8]

Markowitz (1951) asserted the existence of a utility function for income $U(E, V)$, where $dU/dE > 0$ and $dU/dV < 0$ hold. Our model is based on the assumption that $U(E, V)$ exists.

Given the existence of $U(E, V)$, the preference function can be linearized for ease of estimation in the following manner:

$$(1) \quad U(E, V) = E - bV,$$

where $b$ represents the subjective risk coefficient of the farm operator. Now the utility of returns to the farm operator is a direct function of the mean and variance of the returns. An extension of this model can be defined so that the choice object, the maximization of utility of an enterprise portfolio, is quite simple for a two-enterprise case. If the farm operator makes an enterprise decision between two enterprises, the equation for portfolio selection is to maximize:

$$(2) \quad U(Z) = \lambda\mu_x + (1 - \lambda)\mu_y - b\left[\lambda^2\sigma_x^2 + (1 - \lambda)^2\sigma_y^2 + 2(\lambda - \lambda^2)\sigma_{xy}\right],$$

where $Z$ represents the returns from a portfolio of two enterprises, $x$ and $y$. The two enterprises are treated as stochastic variables, where $\lambda \geq 0$ is the fraction of the total portfolio allocated to enterprise $x$, and $1 - \lambda$ is the fraction of the total portfolio allocated to enterprise $y$. In equation (2), $\mu_x = E(x)$ and $\mu_y = E(y)$ represent the expected (mean) returns from enterprise $x$ and expected (mean) returns from enterprise $y$, respectively. The variance of returns from enterprise $x$ is $\sigma_x^2$, and the variance of returns from enterprise $y$ is $\sigma_y^2$. Finally, the covariance of returns from enterprises $x$ and $y$ is $\sigma_{xy}$. Thus, the expected value of returns per enterprise for a two-enterprise portfolio is expressed as

$$(3) \quad E(Z) = \lambda\mu_x + (1 - \lambda)\mu_y,$$

[7] In practice, payments have far exceeded the amounts called for in the 1996 FAIR Act, and the payments made were disbursed based on the ability to earn payments under the 1996 Act (e.g., emergency payments were based on some proportion of AMTA payments).

[8] Several reasons are offered for this approximation: people find it easier to compute (Borch, 1968), distributions facing individuals exhibit little "skewness" (Borch, 1969), or "information costs" on higher-order moments are prohibitive (Gould, 1974).

and the variance of returns from the portfolio is

$$(4)\quad \sigma_z^2 = \lambda^2\sigma_x^2 + (1-\lambda)^2\sigma_y^2 + 2(\lambda - \lambda^2)\sigma_{xy},$$

where $E(Z)$ and $\sigma_z^2$ are simply the mean and variance of the combination of the two enterprises, respectively. For a portfolio consisting of two enterprises, the model will be of the form in equation (2). The farm operator is assumed to maximize $U$, and the decision is to choose $\lambda$ that would lead to this maximization. The first-order condition for the maximization of $U$ is:

$$(5)\quad \frac{dU(Z)}{d\lambda} = \mu_x - \mu_y - b\left[2\lambda\sigma_x^2 - 2(1-\lambda)\sigma_y^2 + (2-4\lambda)\sigma_{xy}\right] = 0.$$

The model presented here could be generalized for more than two enterprises. Assume that the return from the $i$th enterprise is $\tilde{R}_i$, and the farm operator allocates a fraction $\lambda_i$ of the portfolio to enterprise $i$. Then total income is designated by:

$$(6)\quad \tilde{I} = \sum_{i=1}^{n} \lambda_i \tilde{R}_i,$$

which has the following mean and variance:

$$(7)\quad \bar{I} = \sum \lambda_i \bar{R}_i,$$
$$V^2 = \sum \lambda_i^2 \mathrm{Var}(R_i) + 2\sum_{i \neq j} \lambda_i\lambda_j \mathrm{Cov}(R_i, R_j).$$

As a farm operator varies his or her portfolio (i.e., the farm plan), the returns (income) remain normally distributed, though their mean and standard deviation will depend on the choice of the fractions $\lambda_i$. Figure 1 plots the outcome of efficient portfolio choices (those which minimize $V$ for a given $\bar{I}$), and the indifference curves associated with the utility function (lines of constant expected utility). One goal of this analysis is to determine the effect of farm and operator characteristics, soil productivity, government program payments, and distance to market on farm enterprise diversification. An empirical representation of equation (3) that relates diversification to several relevant explanatory variables is given by:

$$(8)\quad Y_i = \mathbf{X}_i\alpha + \phi_i,$$

where $Y_i$ is the entropy index (measure of diversification); $\mathbf{X}_i$ is a vector of farm and operator characteristics, location, soil productivity, and distance to market; $\alpha$ is a vector of unknown parameters to be estimated; and $\phi_i$ is a residual term.

## Empirical Model and Estimation

Estimation of the diversification model as specified by equation (8) is performed based on the following:

$$(9)\quad L_i = \log\left[\frac{Y_i}{1-Y_i}\right] = \alpha_0 + \alpha_1 X_{1,i} + \alpha_2 X_{2,i} + \ldots + \alpha_k X_{k,i} + \phi_i,$$

where log is the natural logarithm operator, $X$ is an explanatory variable, and $\alpha$ is a coefficient to be estimated. Since the values of $Y_i$ are between 1 and 0, and in order to avoid violating the standard assumption about the error term (i.e., $\phi_i$ is required to have a nontruncated normal distribution) which is needed in least squares, a logistic transformation of $Y_i$ is carried out as depicted in $L_i$ [equation (9)]. El-Osta, Bernat, and Ahearn (1995) used a similar transformation of a Gini coefficient to investigate the role of off-farm income in income inequality (also see Fomby, Hill, and Johnson, 1984; Slottje, Hayes, and Shackett, 1992; Greene, 2000).

There are several measures of diversification used in the literature (e.g., concentration ratio, Berry index, Herfindhal index, entropy index). The properties of these measures are discussed in more detail by Hackbart and Anderson (1978) as well as Gollop and Monahan (1991). The entropy index was initially developed in information theory as a measure of the probability distribution or entropy of random variables with a finite sample space, but its application has been

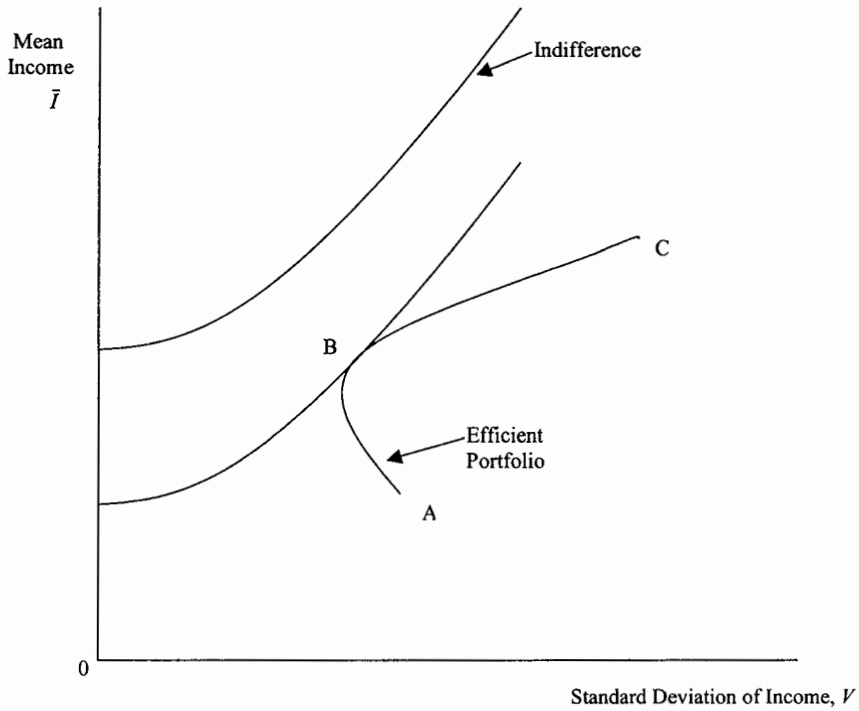


**Figure 1. Mean-Variance Portfolio Choice**

expanded to other sciences. For example, it has been used in studies in ecology on species diversification within habitats, and in economics as a measure of the size disparity of firms (Jacquemin and Kumps, 1971) and of product diversification of firms and corporations (MacDonald, 1985; Carter, 1977; Berry, 1971).

In this study enterprise diversification is measured using an entropy index (Theil, 1971):

$$EINDX = \sum_{i=1}^{N} \begin{pmatrix} \%\ value\ of\ production \\ from\ enterprise\ i \end{pmatrix} \times \frac{\log\left(\dfrac{1}{\begin{pmatrix} \%\ value\ of\ production \\ from\ enterprise\ i \end{pmatrix}}\right)}{\log(N)},$$

where $i$ refers to each of the $N$ possible enterprises. This index accounts for both the mix of commodities and the relative importance of each commodity to the farm business. The entropy index spans a continuous range from 0 to 1. The value of the index for a completely specialized farm producing one commodity is 0. A completely diversified farm with equal shares of each commodity has an entropy index of 1. Specifically, an entropy measure of farm diversification considers the number of enterprises in which a farm participates and the relative importance of each enterprise to the farm. An operation with many enterprises, but with one predominant enterprise, would have a lower number on the diversification index scale. Higher index numbers go to operations that distribute their production more equally among several enterprises.

The model is estimated using weighted least squares. Additionally, a multiplicative dummy variable approach is used to test for statistical difference among regression coefficients over the two time periods considered here (1996 and 2000).

## Test of Equivalency of Separate Coefficients Across Two Regressions

Let the following represent the regression performed on the pooled data (1996 and 2000):

$$(10)\quad L_i = \alpha_0 + \sum_{k=1}^{18} \alpha_k X_k + \delta_{19} D + \sum_{20}^{37} \delta_k D_k X_k + \xi,$$

where, for example, $X_1$ is age of the operator (*OP_AGE*) and $X_{18}$ is the urbanization index (*FRM_URBAN*), and where $D$ is a dummy variable equal to one if the year is 1996 and zero otherwise. Since each of the dummy coefficients $\delta_{19}, \ldots, \delta_{37}$, also known as differential slope coefficients, measures the difference in respective slopes across the two years (1996 and 2000), resulting $t$-tests from the regression performed on equation (10) provide useful information. For example, if the $t$-test corresponding to $\delta_{20}$ (i.e., coefficient of the variable *D*OP_AGE*) indicates $\delta_{20}$ is significantly different than zero, this is equivalent to the finding that the coefficients of the variable *OP_AGE*, which are based on two separate regressions (one for each year, 1996 and 2000), are significantly different. If the resulting $t$-ratio is positively signed, this indicates the *OP_AGE* coefficient in the year 2000 is significantly larger than its counterpart in the year 1996.

## Data

Data for the analysis are pooled from the 1996 and 2000 Agricultural Resource Management Surveys (ARMS). This survey is conducted annually by the USDA's Economic Research Service and National Agricultural Statistics Service. ARMS uses a multi-phase sampling design and allows each sampled farm to represent a number of farms that are similar, where this number is defined as the survey expansion factor. The survey collects data to measure the financial condition (farm income, expenses, assets, and debts) and operating characteristics of farm businesses, the cost of producing agricultural commodities, and the well-being of farm operator households. In addition to collecting basic financial data, ARMS is dedicated to the collection of special data on farms and farm operator households. In 1996 and 2000, ARMS collected information on business contracts by farm operators, management decisions, information sources, use of technology, management strategies, and off-farm employment.

Table 1 presents the definitions and mean values of the explanatory variables and the dependent variable (*EINDX*) for the 1996 and 2000 study years. In general, farms in year 2000 were slightly more diversified than farms in 1996. The average age of the farm operator (*OP_AGE*) in year 2000 was approximately 2½ years higher than the average age of the farm operator in 1996. The average level of education for farm operators (*OP_EDUC*) was similar between the two sample years.

The level of AMTA and LDP[9] government payments (*GOV_PMT*) received by an average farm in 2000 was twice as high as in 1996 (approximately $4,600 in 2000 compared to $2,400 in 1996) (Table 1). In the fall of 2000, Congress wanted to disburse the emergency payments[10] (including supplemental appropriations) to farmers without protracted delay, and therefore emergency payments were directed to farmers who were already receiving AMTA payments. Since emergency payments (including supplemental appropriations) were based

[9] Other types of government payments, such as conservation, disaster, and other payments, are not included because the latter two in particular are not anticipated at the start of the growing season, and therefore are not assumed to influence production decisions.

[10] Under normal circumstances, to receive any emergency payments, farmers must go through the usual application, certification, and qualification process that is laid out by the Farm Service Agency.

**Table 1. Definitions and Means of Variables Used in Weighted Least Squares Models**

| Variable | Definition | Mean 1996 | Mean 2000 |
|---|---|---|---|
| *OP_AGE* | Age of farm operator (years) | 52.68 | 55.25 |
| *OP_EDUC* | Educational level of farm operator | 12.63 | 12.55 |
| *HH_SIZE* | Size of the farm household (number of persons) | 3.00 | 2.71 |
| *OP_GEND* | Gender of farm operator (= 1 if male; 0 otherwise) | 0.92 | 0.88 |
| *HAV_INSUR* | = 1 if the farm has crop or farm business insurance; 0 otherwise | 0.81 | 0.79 |
| *HAV_CONTR* | = 1 if the farm has a production or a marketing contract; 0 otherwise | 0.12 | 0.10 |
| *GOV_PMT* | Total AMTA and LDP payments received by the farm ($10,000s) | 0.24 | 0.46 |
| *FRM_SIZE* | Value of agricultural production sold by the farm ($10,000s) | 8.23 | 6.97 |
| *OFF_WAGE* | Off-farm income (income from wages and salaries) ($10,000s) | 2.62 | 3.37 |
| *DEBT_ASST* | Debt-to-asset ratio | 0.15 | 0.11 |
| *WRK_STAT* | = 1 if the farm operator works full time on the farm (2,000 hours or more); 0 otherwise | 0.30 | 0.28 |
| *FRM_SOLE* | = 1 if the farm is organized as a sole proprietorship; 0 otherwise | 0.87 | 0.92 |
| *FRM_PART* | = 1 if the farm is organized as a partnership; 0 otherwise | 0.06 | 0.05 |
| *F_NEAST* | = 1 if the farm is located in the Northeast region of the U.S.; 0 otherwise | 0.06 | 0.07 |
| *F_MWEST* | = 1 if the farm is located in the Midwest region of the U.S.; 0 otherwise | 0.09 | 0.10 |
| *F_WEST* | = 1 if the farm is located in the Western region of the U.S.; 0 otherwise | 0.19 | 0.20 |
| *FRM_PROD* | Mean productivity index of the farm | 73.76 | 72.98 |
| *FRM_URBAN* | Urbanization index, based on the proximity of the farm to an urban area | 1.84 | 1.82 |
| *EINDX* | Dependent variable, measure of diversification (Entropy Index) | 0.15 | 0.17 |
| Sample Size | | 6,548 | 9,863 |

on an individual farm's AMTA payments, these emergency payments are included in total AMTA payments.

Average value of agricultural products sold by the sample farms (*FRM_SIZE*) fell from $82,300 in 1996 to $69,700 in 2000. Finally, the data show that the number of full-time farm operators (*WRK_STAT*) decreased between the two years, from 30% in 1996 to 28% in 2000.

Correspondingly, income from off-farm wages and salaried jobs (*OFF_WAGE*) increased by 29%, from $26,200 in 1996 to $33,700 in 2000 (Table 1).

## Results

Weighted least squares estimates of factors affecting farm enterprise diversification as depicted in equation (9), for 1996 and 2000, are presented in Table 2.

**Table 2. Weighted Least Squares Estimates for Factors Affecting Farm Diversification, 1996 and 2000**

| | Diversification (*EINDX*) | | | | |
|---|---|---|---|---|---|
| | Parameter Estimates, 1996 | | Parameter Estimates, 2000 | | $H_0$: $\alpha_{1996} = \alpha_{2000}$ |
| **Variable** | $\alpha_{1996}$ | *t*-Statistic [a] | $\alpha_{2000}$ | *t*-Statistic [a] | *t*-Statistic [b] |
| Intercept | -9.564*** | 5.12 | -9.506*** | 4.15 | |
| *OP_AGE* | -0.010** | 2.14 | -0.013** | 1.93 | -2.03** |
| *OP_EDUC* | 0.059 | 1.15 | 0.064 | 0.51 | 0.78 |
| *HH_SIZE* | 0.105*** | 2.59 | 0.146*** | 3.19 | 0.81 |
| *OP_GEND* | 0.298 | 1.26 | -0.008 | 0.41 | -0.27 |
| *HAV_INSUR* | 0.454*** | 2.92 | 0.669*** | 2.95 | 5.49*** |
| *HAV_CONTR* | 1.973 | 1.13 | 0.623 | 0.55 | -5.77** |
| *GOV_PMT* | 0.350* | 1.69 | 0.300*** | 3.09 | -2.81*** |
| *FRM_SIZE* | -0.002*** | 3.63 | -0.001*** | 3.26 | 0.39 |
| *OFF_WAGE* | -0.013 | 1.35 | -0.039** | 2.90 | -2.94*** |
| *DEBT_ASST* | -0.722*** | 2.72 | -0.104** | 2.00 | 3.05*** |
| *WRK_STAT* | 1.994*** | 3.45 | 1.924*** | 3.54 | -2.34** |
| *FRM_SOLE* | 0.418** | 2.36 | 0.354** | 2.44 | -0.90 |
| *FRM_PART* | -0.239 | 0.70 | -0.105 | 0.25 | 0.57 |
| *F_NEAST* | 0.356* | 1.81 | 1.015** | 2.08 | 4.07*** |
| *F_MWEST* | 1.711** | 1.96 | 1.762** | 2.19 | 1.31 |
| *F_WEST* | 1.398 | 1.21 | 1.598 | 0.96 | 0.93 |
| *FRM_PROD* | 0.033*** | 4.40 | 0.038*** | 4.19 | 0.34 |
| *FRM_URBAN* | -0.094** | 2.09 | -0.241* | 2.44 | -0.61 |
| Adjusted $R^2$ | 0.19 | | 0.22 | | |

*Note:* Single, double, and triple asterisks (*) denote two-tailed statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.

[a] Reported *t*-statistics are absolute values.

[b] Each *t*-statistic in this column tests the hypothesis that a specific estimated parameter in the farm diversification model of 1996 is equal to the corresponding parameter in the 2000 farm diversification model. A negative statistically significant *t*-statistic indicates that the corresponding $\alpha_{2000}$ is statistically smaller than its $\alpha_{1996}$ counterpart. A positive statistically significant *t*-statistic shows the opposite (i.e., $\alpha_{2000} > \alpha_{1996}$).

The adjusted $R^2$s of 0.19 and 0.22 for 1996 and 2000, respectively, indicate that the explanatory variables used in the weighted least squares regression model explained 19% and 22% of the variation in farm diversification. These levels of explained variation are fairly typical when analyses are based on cross-sectional data. In 1996, the estimated model in equation (9) reveals that 12 variables are significantly correlated with farm diversification.

The *t*-test results presented in the final column of Table 2 were obtained using the multiplicative dummy variable approach (see Pindyck and Rubinfeld, 1991). This *t*-test is used to highlight any significant parameter differences across the 1996 and 2000 time periods. Based on the values of the *t*-statistics, use of insurance, amount of government payments received, financial position, off-farm income, or whether the farm is located in the Northeast are all variables that exhibit strong statistical difference between the two time periods. Additionally, age of operator, whether the operator is a full-time farmer, or uses marketing or production contracts are variables also showing statistical difference across the two periods.

Farm size measured by the value of agricultural products sold by the farm (*FRM_SIZE*) is significant and inversely related to farm diversification (*EINDX*) in both study years. This result is consistent with those reported by White and Irwin (1972), but contrasts with findings that diversification activities are concentrated on large farms (Pope and Prescott, 1980; Gasson, 1988a, b; Ilbery, 1991; Shucksmith and Smith, 1991). The suggestion that larger farms may be more specialized is consistent with an argument based on economies of scale—i.e., if there are large-scale economies in an enterprise, then one might expect large farms to be more specialized. Another possible explanation is that since farm size and wealth tend to be positively correlated, one can deduce that wealthier farms are less risk averse and less diversified—all else being equal. This position is supported by Pope and Prescott (1980) who report a negative and significant relationship between wealth and farm diversification.

The coefficient for age of the farm operator (*OP_AGE*) is negative and statistically significant at the 5% level for both the 1996 and 2000 models. Results suggest that older farm operators are less likely to diversify. One possible explanation is that older farm operators have more wealth, and wealthier farm operators are less risk averse and less diversified (Pope and Prescott, 1980). In contrast, young and beginning farm operators are more risk averse and are in the wealth accumulation phase of their life cycle. But more plausibly, young farmers may start small and diversified, and perhaps become more specialized as they expand their operation.

The size of the farm household (*HH_SIZE*) is included in the analysis because Bowler et al. (1996), among others, report that the need to create employment for family members is one of the important factors motivating farm diversification. Additionally, Damianos and Skuras (1996) note the size of the farm household may be an indication that diversified farms are at an earlier stage in the life cycle. This is the stage when farmers tend to make the greatest change to the farm business (Potter and Gasson, 1988). Based on the results of our study, the size of the farm household and diversification are positively correlated in both models (1996 and 2000). These results are consistent with the findings of Damianos and Skuras (1996); Bowler et al. (1996); and McNally (2001).

The debt-to-asset ratio (*DEBT_ASST*) can be used as a measure of leverage. The coefficient of *DEBT_ASST* is negative and statistically significant in both models (1996 and 2000). This result suggests farms with a higher debt-to-asset ratio are less diversified. Higher debt-to-asset ratios are often associated with energetic and dynamic farmers, or entrepreneurs and innovators (Bowler, 1992). Another possible explanation is that a high level of debt might also be indicative of the farm business having borrowed in order to upgrade the commitment to agriculture by adopting the latest production technology for a specific enterprise with the goal of expanding output to capture economies of scale. These results also reveal, based on equivalency tests, that the impact of the debt-to-asset ratio on diversification was stronger in 2000 than in 1996.

Government payments play an important role in production agriculture and the survival of farms. For example, in 2000, government payments played a major role in stabilizing gross and net income of U.S. farms. The bulk of these government payments were provided, under the existing 1996 FAIR Act, through three specific forms of direct payments: production flexibility contract payments (which replaced most commodity program payments), loan deficiency payments, and emergency supplemental appropriations (specifically those enacted in October 2000). Federal direct payments to farmers totaled approximately $23 billion in 2000, with 22% of this amount in the form of production flexibility payments, 28% in loan deficiency payments, and the remainder primarily in the form of emergency assistance payments.

The coefficient of *GOV_PMT*—which captures total AMTA (including production flexibility and emergency assistance payments) and LDP payments received by the farm—is positive and significant in both the 1996 and 2000 models. The results also indicate, based on equivalency tests, the impact of government payments on diversification was stronger in 1996 than in 2000. These findings suggest government payments and enterprise diversification are complementary risk-reduction strategies.

Other studies have concluded that receiving payments from government programs is a primary risk-reducing mechanism (Kramer and Pope, 1981; Musser and Stamoulis, 1981). As Goodwin and Schroeder (1994) note, government programs are intended to decrease agricultural producer risks. In addition, Robison and Barry (1987) point out that government programs emphasize the provision of risk-reducing opportunities for the farm.

The coefficient of off-farm income from wages and salaries (*OFF_WAGE*) is negative in both models, but statistically significant only in the 2000 model. The combination of low farm income, represented by a reduction in average value of agricultural products sold in 2000, and a strong nonfarm economy encouraged many farm operators and their spouses to work off the farm. This is reflected in a 29% increase in off-farm wages and salaries between 1996 and 2000. This view is further supported by the fact that the average number of farm operators working full time on the farm decreased in 2000. Additionally, Mishra and Goodwin (1997) found a positive relationship between the coefficient of variation for farm income and off-farm work. Specifically, the greater the variability of farm income, the higher the farm operators' off-farm labor participation rate. Off-farm income diversifies a farm operator's income portfolio and reduces the need for enterprise diversification. In many cases, off-farm work is not compatible with the labor demands of farm enterprise diversification. This is consistent with the findings of Calvin (1992); Just and Calvin (1990); and Mishra and Sandretto (2002). A negative and significant coefficient of *OFF_WAGE* in the 2000 model supports the potential ability of farmers to self-insure.

Table 2 shows there is a positive and significant relationship between diversification and full-time farm operators (*WRK_STAT*). Results indicate a full-time farmer is more likely to diversify compared with a part-time farm operator. Full-time farmers demonstrate a commitment to farming, and therefore desire to employ the available labor more uniformly throughout the course of a year in addition to diversifying risk on the farm. Another explanation could be that full-time farm operators are involved in labor-intensive farming,[11] such as dairy, which leaves very little time to work off the farm. Other full-time operators may be constrained from seeking off-farm work because of age, disability, location, or other factors.

Purchase of insurance, crop insurance or revenue insurance, is a private risk management strategy farmers have used to reduce risk and uncertainty associated with farm income (Harwood et al., 1999). The coefficient of farm insurance (*HAV_INSUR*) is positive and statistically significant at the 1% level for both 1996 and 2000, indicating farmers who buy insurance operate diversified farms. This may be a case of a farm operator who is risk averse and reduces risk in several ways (Goodwin and Schroeder, 1994). This result demonstrates the farm operator's ability to self-insure and bolsters the view that insurance and diversification are complements (Mishra and Goodwin, 2003).

A positive and significant correlation is found to exist between farm diversification and the legal form of business organization,

[11] Farmers involved in highly seasonal production activities, such as cash grains, have more time to pursue nonagricultural activities—both on and off their farms.

particularly if the business is organized as a sole proprietorship (*FRM_SOLE*), when compared with other forms of business organization.[12] In the case of sole proprietorship, the farm operator has much at stake in the form of capital financing (unlimited personal liability for the business's debts) and there is no risk sharing. Therefore, it is not surprising for a sole proprietor to diversify the farm, given that diversification is a private risk management strategy. Further, sole proprietorship is the most common form of business organization on small and medium-sized farms, and these farms (small and medium) are more likely to be diversified as evident from the results reported above.

Aside from farm, operator, and household characteristics, soil productivity and distance to an urban area are also factors that may affect farm diversification. For example, if the soil is productive and can produce several crops, then the farm operator might be inclined to try new crops and other enterprises on the farm. Crop diversification through the use of rotations suited to the site-specific conditions at the field level has been demonstrated to be beneficial in protecting soil quality and productivity over the long term and can contribute to higher and more stable net farm income (Clark, 2001; Zentner et al., 2002). The coefficient of the mean productivity index (*FRM_PROD*) is positive and significant for both models at the 1% level.

Previous work on farm diversification has highlighted the importance of proximity to main roads and urban centers for development of other farm enterprises (Ilbery, 1991; Shucksmith et al., 1981; Edmond, Corcoran, and Crabtree, 1993). Such access is assumed to provide the market stimulus for the development of farm enterprises. Results show a negative and significant correlation between farm diversification and proximity to an urban area (*FRM_URBAN*) in both models.

[12] Other forms of business organization included family corporations, which acted as the benchmark.

Operators and family members of farms located near urban areas are more likely to work off the farm. One interpretation is that off-farm work is a substitute for onfarm enterprise diversification. This is evident from the negative and significant correlation between off-farm work and diversification in the 2000 model. Additionally, farms located near urban areas tend to specialize in niche products.

Finally, geographic location determines rainfall, soil productivity, and access to markets, which in turn influences potential cropping patterns. Four regional dummies to indicate location of the farm were defined, and three were included in the regression. However, only the coefficients of *F_MWEST* and *F_NEAST* were statistically significant in both the 1996 and 2000 models. Thus, compared to farms in the South (the benchmark), Midwestern and Northeastern farms are found to be more likely to diversify.

## Summary and Conclusions

The objectives of this study were to determine if there was a discernable difference in the level of enterprise diversification in two time periods (1996 and 2000), and to identify those farm, operator, and financial characteristics that are correlated with farm enterprise diversification. This study has used national farm-level data (1996 and 2000) with great diversity regarding farm size, location, commodities produced, and risk management strategies (such as crop insurance, participation in production and marketing contracts, and off-farm income). In general, farms in 2000 had slightly more diversified farm enterprises than farms in 1996. This finding would support the argument that the "freedom to farm" production flexibility provisions in the FAIR Act of 1996 may have contributed to enterprise diversification.

Evidence reported here suggests diversification and farm size may be negatively correlated. These findings are consistent with economic theory in confirming that economies of scale exist in

production. In addition, results show that older farm operators, farm households with off-farm income (from wages and salaries), farms with higher debt-to-asset ratios, and farms located near urban areas are less likely to diversify farm enterprises. In contrast, evidence suggests there is a significant positive relationship between farm enterprise diversification and family size, having crop insurance or farm business insurance, and being a sole proprietor and a full-time farmer. Finally, farms that received government commodity program payments are found to be more diversified than their nonparticipating counterparts.

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# Competition in Farm Credit Markets: Identifying Market Segments Served by the Farm Credit System and Commercial Banks

*Charles B. Dodson and Steven R. Koenig*

## Abstract

Agricultural credit markets are dominated by two institutional retail lender groups, the cooperative Farm Credit System (FCS) and commercial banks. Analysis of farm loans made over the 1991–1993 and 2001–2002 periods indicates that FCS lenders were more likely to serve full-time commercial farmers and farmers located in regions with less competitive credit markets. In contrast, commercial banks were more likely to serve small, part-time, and hobby farmers. This segmentation of farm credit markets is consistent with federal regulations requiring the FCS to provide credit to "*bona fide*" farmers with a basis for credit.

*Key words:* agricultural banks, farm credit markets, Farm Credit System, farm lenders, market segmentation

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Commercial banks and the cooperative Farm Credit System (FCS) are the primary suppliers of agricultural credit to U.S. farmers. During the 1990s, their importance as sources of agricultural credit grew. The share of farm business debt provided by the two lender groups rose from 61% in 1991 to over 70% by 2003 [U.S. Department of Agriculture/ Economic Research Service (USDA/ERS), 2003]. Much of the remaining credit supplied to the farm sector comes from USDA's Farm Service Agency (FSA), life insurance companies, individuals, and input suppliers. These other lenders often serve niches within the agricultural credit market and are less likely to be direct competitors with either the FCS or banks.

While banks and FCS are commonly viewed as direct competitors in farm credit markets, past studies report that farm credit markets are segmented, with FCS lenders more likely to serve "larger, wealthier, and more established farmers," and banks more likely to serve smaller and part-time farms (Dodson and Koenig, 1994; Ryan and Koenig, 1999).

A better understanding of the market segments served by these two dominant lender groups should provide insight as to the potential role of subsidized credit programs, such as those administered by the USDA. Specifically, are the FCS and commercial banks meeting the credit needs of groups considered more likely to have limited access to credit, such as farmers in less competitive lending markets, young or beginning farmers,

racial and ethnic minority farmers, and other farmers with limited financial resources? Based on findings of earlier studies, one might conclude that the FCS has chosen to lend primarily to lower risk segments of the farm credit market. But differences in FCS and bank borrowers may simply reflect these lenders' relative comparative lending advantages—i.e., lenders are more likely to focus on the market segments where they have the greatest comparative advantage.

In this study, farm-level data from USDA's Agricultural Resource Management Survey (ARMS) and its pre-1996 predecessor, the Farm Costs and Returns Survey (FCRS), are used to assess the presence of market segmentation among FCS and banks by analyzing the characteristics of their new borrowers from 1991 to 1993 and from 2001 to 2002. The analysis then examines how market segmentation by the FCS and banks may have been influenced by federal policies, the competitiveness of local credit markets, lender organizational structure, and loan targeting requirements. The two periods were selected to determine whether segmentation may have changed over time due to structural changes in agriculture or financial markets.

## Market Segmentation and Farm Credit Markets

Market segmentation has been defined as the division of a market into homogeneous groups in order to identify customers most likely to purchase products or services offered. Market segmentation has been used increasingly since the 1950s to differentiate products, expand sales, and obtain competitive advantages in the market place (Wedel and Kamakura, 1999). Continuing improvements in information technology have enhanced the abilities to identify and reach potential consumers with more customized offerings of goods or services at ever lower costs. Successful market segmentation requires significant and measurable differences among customers. Differences among consumers typically used to segment markets include demographic variables such as age, sex, race, income, occupation, education, household status, and geographic location. Psychographic variables such as lifestyle, activities, interests, and opinions have also been successfully used to segment markets.

Historically, agricultural lenders have segmented markets by geographic location, enterprise type, loan size, or credit risk (Boehlje, 1998). Each group represented in a market segment must seek unique benefits which can be met through products or services provided by the marketer (lender). Structural change in agricultural production combined with the financial market deregulation and information technology advancements have significantly improved the ability of lenders to focus on market segments where they have had the greatest competitive advantage (USDA/ERS, 1997). Technological advances have increased the availability of information and lowered transaction costs, thereby enabling lenders to sharpen their marketing efforts. By removing geographic and industry barriers, financial deregulation has allowed lenders to expand their marketing efforts into new regions and new industries (Executive Office of the President of the United States, 2003).

In general, credit markets benefit from market segmentation through greater efficiencies. But, these benefits may be less apparent among groups who remain costly to serve. Lenders may be less willing to serve market segments with limited credit history, such as young and beginning farmers. These market segments often require additional loan servicing and may be adversely affected by greater market segmentation. Also, some lenders may be less willing to lend to segments located in regions where the potential volume is insufficient to justify the additional expense of maintaining a branch office.

Aided by financial deregulation, banking consolidation has resulted in fewer banks, especially in rural areas (Avery et al., 1997).

Consequently, farmers in sparsely populated areas may be more likely to face imperfect competition for their credit needs. Yet, technology advances, such as internet-delivered financial services, have increased the presence of nonbank financial institutions and reduced the importance of physical location.

Past studies have found farm credit markets are segmented among lenders based on farm, nonfarm, and operator characteristics. Dodson and Koenig (1995) used operator age, occupation, farm sales, net worth, and off-farm incomes to identify various niches in farm credit markets. Moss, Barry, and Ellinger (1997) used similar criteria to describe three potential market segments consisting of large-scale producers, small-scale producers, and industrial units. Both studies concluded the credit needs of part-time farmers are different from those of full-time commercial farmers.

In their 1994 study of major farm lenders, Dodson and Koenig found that FCS-held debt in 1991–92 was more likely to be owed by larger, older, wealthier, and higher income operators when compared to commercial bank-held farm debt. Ryan and Koenig (1999), using 1997 data, found that FCS-held debt was concentrated in larger farming operations which were more financially secure. Using 1999 data, Ryan and Koenig (2001) reaffirmed the findings of their earlier study. However, while these studies contrasted the characteristics of bank and FCS borrowers, there was no attempt to determine if group differences were statistically significant. Moreover, these studies examined the characteristics of all outstanding loans and not just new loans made by these two lender groups. Recently originated loans would be more likely to reflect current lending policies.

## Segmentation Model

The model developed for this analysis tests for the presence of market segmentation of farm credit markets by the two dominant lenders to U.S. agriculture: commercial banks and the Farm Credit System. If these two primary lender groups segment the markets, then identifiable differences should occur between the borrowers and the markets they choose to serve. This analysis improves upon previous research by examining only new loans originated over a specific period and by evaluating differences through statistical tests. The model developed for this analysis tests the null hypothesis that the attributes associated with new FCS borrowers are no different than the attributes associated with new commercial bank borrowers receiving loans during the same time period. As such, any differences in the attributes of FCS and bank borrowers would be consistent with the occurrence of market segmentation.

Multivariate techniques such as clustering, conjoint analysis, or factor analysis are commonly used to identify post hoc market segments. For determining the a priori existence of market segments, logit, probit, or discriminate analyses have been used. Based on the statistical significance of summary statistics from a multinomial probit model, Black and Schweitzer (1981) assessed market segmentation of home mortgage markets among commercial banks and mutual savings banks. In the current study, a multivariate logit model is used to examine market segmentation of farm credit markets between the FCS and commercial banks. As with Black and Schweitzer, significance of model summary statistics is considered to be consistent with the presence of market segmentation.

In the estimated multivariate logit model, the dependent variable *FCSMEAN* was equal to 1 if a majority of the farm operator's debt originated during the study period was provided by FCS, and was equal to 0 if the majority was provided by banks.[1] As such, *FCSMEAN* = 1 corresponds to the

[1] A majority of debt was defined as a borrower having at least 50% of his or her total debt from a particular lender group. Ryan and Koenig (2001) have shown that most farm borrowers rely on one lender for their credit needs.

group of new farm borrowers included in the FCS market segment, while *FCSMEAN* = 0 corresponds to a group of new farm borrowers in the bank market segment.

The expectation as to which particular segment a new farm borrower belongs was hypothesized to be a function of a set of variables related to federal policies, the competitiveness of local credit markets, lender organizational structure, and loan targeting requirements. The model is estimated over two time periods (1991–1993 and 2001–2002) to determine whether segmentation had changed over time due to structural changes in farming and farm credit markets.

## Federal Policy Variables

Federal laws and regulations may foster an environment where the FCS is more likely to serve commercial-size farms, while commercial banks are more likely to serve small or part-time farms. This might be because federal statutes and regulations limit eligibility to FCS loans and the types of financial products it may offer. The Farm Credit Act of 1971 requires the FCS to serve only "*bona fide farmers and ranchers.*" A bona fide farmer or rancher is defined as a person owning agricultural land or engaged in the production of agricultural products, including aquatic products under controlled conditions [U.S. Code 12CFR613.3000]. Regulations also stipulate that FCS institutions provide full credit, to the extent of creditworthiness, to full-time bona fide farmers for agricultural enterprises [U.S. Code 12CFR613.3005]. While there are no explicit limitations on providing credit to part-time farmers, current Farm Credit Administration (FCA) regulations stipulate that FCS lenders are to provide only "conservative" credit to these farmers.

FCA regulations also limit FCS financial products and services to such areas as farm tax preparation, equipment leasing, estate planning, providing crop insurance, and farm appraisal services. Unlike a full-service bank, FCS lenders may not directly provide financial services such as checking, investments, certain insurances, or business loans that are not related to farming.[2] Banks may have a comparative advantage over the FCS in meeting the needs of part-time farmers because of the wider array of financial services they can offer and their greater expertise in evaluating the risks of lending to part-time farmers. For part-time and small farms, consumer credit and investment services available from banks are likely to be more important to choosing a lender than the farm credit services or expertise offered.[3] Therefore, it is hypothesized operators of full-time commercial-size farms are more likely to benefit from the financial products and services provided by the FCS or the agricultural knowledge and expertise of an FCS loan officer, whereas small and part-time farms are more likely to demand bank services.

Current FCA regulations do not provide a conclusive definition of a full-time bona fide farmer. Research conducted by USDA's Economic Research Service has considered full-time status to be associated with factors such as the operator's primary occupation, the number of labor hours devoted to farming, the reliance on the farm enterprises for total household income, and the size of the farm (Hoppe, Perry, and Banker, 2000).

To identify full-time commercial and part-time farmers, four mutually exclusive categories of farmers were developed (Table 1). A full-time commercial farmer (*FULLTIME*) is defined as someone who considers farming to be his or her primary occupation, is fully employed by the farm business, is reliant on the farm business

[2] Some FCS lenders partner with other financial institutions to deliver these types of financial products and services.

[3] While banks have no specific regulations governing which segments of the market they serve, the Community Reinvestment Act (CRA) does encourage banks to serve a broad clientele base in their market area. Larger banks serving rural markets may have more of an incentive to serve small farming operations because CRA reporting requirements are more likely to apply to them.

**Table 1. Variable Names, Definitions, and Expected Influence on Segment Outcomes**

| Variable Name | Definition | Lender |
|---|---|---|
| | **— Federal Policy Variables —** | |
| *FULLTIME* | Equal to 1 if primary occupation is farmer, annual operator labor hours >1,500, > 50% of household income is from the farm business, and annual farm sales > $250,000 ($200,000 for 1991–1993); otherwise = 0 | FCS |
| *FAMFARM* | Equal to 1 if meets *FULLTIME* definition, except annual farm sales between $100,000 ($80,000 for 1991–1993) and $250,000; otherwise = 0 [variable omitted for estimation purposes] | Both |
| *PARTTIME* | Equal to 1 if primary occupation is farmer, annual sales < $100,000 ($80,000 for 1991–1993), annual operator labor hours <1,000 hours, and median household income < 200% of county median; otherwise = 0 | Bank |
| *HOBBY* | Equal to 1 if annual sales < $100,000 ($80,000 for 1991–1993) and not considered as part-time (*PARTTIME*); otherwise = 0 | Bank |
| *PURCH* | Share of loans to fund purchases of real estate or equipment | FCS |
| | **— Lender Competition Variables —** | |
| *NO_COMPETITION* | Equal to 1 if farm is located in a county where there are no commercial or savings bank branches making agricultural loans; otherwise = 0 | FCS |
| *FARM_SHR* | Share of total population residing on farms | Bank |
| *MED_HHI* | Equal to 1 if county average household income < $32,000 ($24,000 for 1991–1993); otherwise = 0 | FCS |
| | **— Organizational Variables —** | |
| *DA_RATIO* | Total year-end debt divided by year-end assets | —[a] |
| *TDBTCOV* | Term debt coverage ratio | —[a] |
| *ROA* | Return on assets | —[a] |
| *LOW_CAP* | Equal to 1 if net worth per dollar of annual sales in the lowest quartile; otherwise = 0 | Bank |
| *2ND_CAP* | Equal to 1 if net worth per dollar of annual sales in the second quartile; otherwise = 0[b] | —[a] |
| *MED_CAP* | Equal to 1 if net worth per dollar of annual sales in the third quartile; otherwise = 0 | FCS |
| *HI_CAP* | Equal to 1 if net worth per dollar of annual sales in the highest quartile; otherwise = 0 | Bank |
| *VULNERABLE* | Equal to 1 if total household income is below poverty level and debt-to-asset ratio is greater than 0.40; otherwise = 0 | —[a] |
| | **— Targeting Variables —** | |
| *RACE_ETHNIC* | Share of total farm population in county classified as members of racial or ethnic minority group | FCS |
| *BEG_YOUNG* | Equal to 1 if primary operator < 36 years of age or has < 10 years of farming experience; otherwise = 0 [for 1991–1993 data, = 1 if primary operator < 36 years of age; otherwise = 0] | FCS |
| *OVER_55* | Equal to 1 if primary operator > 55 years of age; otherwise = 0 | Bank |

[a] There is no a priori expectation.

[b] The second quartile was omitted from the model to allow estimation.

for most of the family's income, and has annual farm sales greater than $250,000.[4] For 1991–1993, the minimum annual sales threshold for full-time commercial farms was $200,000, approximately equivalent to the $250,000 threshold after adjusting for general increases in farm size occurring over the time period.

For 1991–1993, the $100,000 sales threshold was adjusted to $80,000 to reflect changes in farm size over the time period. A family-size commercial farm (*FAMFARM*) was distinguished from a full-time commercial farm by limiting annual farm sales to between $100,000 and $250,000. Many farmers within this group would be considered *full-time bona fide farmers* for FCS purposes, though many are part-time farmers. Given such a mix, it was considered to be indeterminate whether this group would be more likely to fall within either the bank or FCS market segment.

Part-time farms (*PARTTIME*) are defined as those with annual farm sales of less than $100,000 ($80,000 for 1991–1993), where the primary operator considered farming to be his or her occupation, and the primary operator supplied less than 1,000 hours of labor annually to the farm business. Also, the total household income of the primary operator had to be less than twice the county average. The part-time farmer group was defined to capture small farms that were more likely to be operated as a farm business rather than as a hobby or a lifestyle farm. While these farmers may meet the regulatory requirement of a bona fide farmer, nonfarm financial products and services are likely to be more important in their selection of a lender than farm financial products and services. Consequently, it is expected that members of this group are more likely to fall within the bank market segment.

Farms defined as hobby or lifestyle (*HOBBY*) included those with less than $100,000 ($80,000 for 1991–1993) in annual farm sales that were not already defined as part-time farmers. Hobby farmers were considered the least likely to be full-time bona fide farmers and least likely to value farm financial products and services. Therefore, a greater share of this group was expected to be found in the bank segment.

FCS loans are primarily intended for farm and farm-related purposes, such as purchases of farmland or farm machinery. Due to its charter and funding mechanisms, FCS has traditionally had a comparative advantage in pricing long-term credits. Refinancing existing indebtedness may not be considered an appropriate use of FCS loan funds, if existing indebtedness arose from nonfarm purposes. The USDA's ARMS data include information on whether the new loans were used to refinance existing indebtedness or to fund new purchases (*PURCH*).[5] It was expected that the FCS would be more likely to make loans used to fund purchases of farm real estate or equipment and less likely to fund loans used to refinance existing indebtedness.

## Lender Competition Variables

As the first government-sponsored enterprise (GSE), Congress established the Farm Credit System to ensure that farmers with the basis for credit have access to farm credit in all areas.[6] Since FCS offices were presumed to be accessible from all counties, farms in counties where farm credit markets may be less competitive were considered more likely to fall within the FCS market segment. With the exception of a few counties in more remote areas, all counties were within 50 miles of an FCS branch office in 2003 (Figure 1).[7]

[4] The $250,000 threshold was chosen to reflect the criteria utilized by the USDA's National Commission on Small Farms (USDA, 1998).

[5] This information was not available in the 1991–1993 FCRS data.

[6] The Farm Credit Act of 1971 specifies that all counties and municipalities in the United States and Puerto Rico shall have access to FCS credit.

[7] Initially, Farm Credit System branches along with bank branches were considered as an indication of competitiveness within a county. A problem arises, however, when one tries to define the region served by

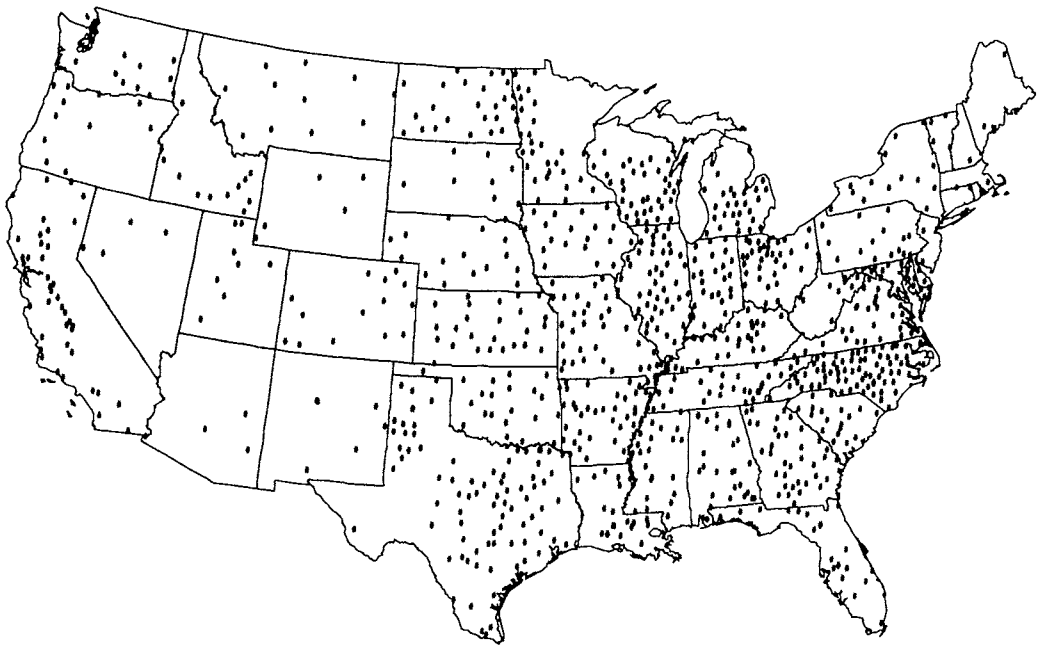


**Figure 1. Location of FCS Association Branch Offices (2003)**

Even those areas or counties without an FCS branch office may have been served through contact points, which are temporary offices staffed only on designated days.

In 1934, Galbraith outlined the important effect that bank branching and bank charters had on the supply of agricultural credit in rural areas during a period when more restrictive lending rules prevailed. Today, commercial bank charters have no geographic lending limitations. Thus, if banks collectively choose not to serve certain geographic regions, competition for farm loans may suffer.[8] Because the commercial banking system remains the largest supplier of debt capital to agriculture, the presence within a county of banks or branch offices of banks which make farm loans should be an indicator of potential market competitiveness.[9]

Given current banking structure, it can be difficult to determine if a county is served by a bank branch that makes farm loans. In a bank's call reports to regulators, bank lending activity is aggregated to the county of the bank's main office and not the counties where branches are located and loans are made. Smaller banks making agricultural loans may have only a few branches and serve a limited geographic area, and therefore are easily identifiable as a source of agricultural loans within a county. But for larger banks, agricultural loans are likely reported in a metro area hundreds of miles distant from where the

each FCS branch office. There are about 1,000 FCS branches dispersed throughout the country. Each of these offices serves a market area that is likely to include multiple counties. Considering the market area to include all counties within 50 miles of an FCS branch resulted in few counties not being located in an FCS branch market area. We took this to be an indication that FCS was indeed present in all locales, and therefore could justify the assumption of nationwide market presence based on its charter.

[8] While interstate banking and branching exists today, in the earlier period of the study (1991–1993) interstate banking was more restrictive, thereby placing geographical barriers on some banks.

[9] While credit unions may provide competition to local markets, the handful of credit unions active in farm lending was deemed to be sufficiently small so as to not bias the model estimations. At mid-2002, only 64 credit unions reported outstanding farm loan volumes in excess of $1 million.

loan was actually made. Because large banks' share of total bank lending is sizable and growing, their influence on agricultural credit market competitiveness is substantial and should not be ignored due to data limitations.[10] Past research has shown that the size and number of bank branches in agricultural areas are important indicators of the agricultural loan levels of large banks (Levonian, 1995). Thus, branches of a large bank with a significant volume of agricultural loans can be an indicator of the presence of an agricultural lender within a county.

To measure bank lending competition in local farm credit markets given the limitations of banking data, the number of banking institutions providing agricultural loans within each county was estimated using the following criteria. An agricultural lender was considered to be present in the county if either of the following two conditions were met: (*a*) the bank's farm loans were at least 10% of its total loans and it had at least one branch office within the county;[11] or (*b*) the bank had at least $50 million in agricultural loans outstanding and maintained at least one branch office in a rural county with a sizable farm population. A rural county was considered to be located 20 miles or more outside an urban cluster, as defined by the U.S. Department of Commerce. A sizable farm population for a county is one having more than 350 indebted farmers, as reported in the *Census of Agriculture* for 1992 or 2002 (USDA, National Agricultural Statistics Service). The first condition is intended to capture smaller community banks that make agricultural loans. The second condition is intended to capture larger regional or nationwide banks that make agricultural loans, while screening out branches in more urban areas which were less likely to make farm loans.

Each county was then classified as to its competitiveness for farm lending. A county was considered competitive if three or more banks meeting either of the aforementioned conditions were present in the county over the entire study period.[12] Using this criterion, slightly less than one-third, or 945, of all counties were considered highly competitive over the 2001–2002 period, while 839 counties were characterized as highly competitive over the 1991–1993 period. These highly competitive counties were concentrated in farm regions of the western Corn Belt and Great Plains. Highly competitive lending markets were also found in Texas, California, Florida, Georgia, Pennsylvania, Washington, and the Mississippi Delta.

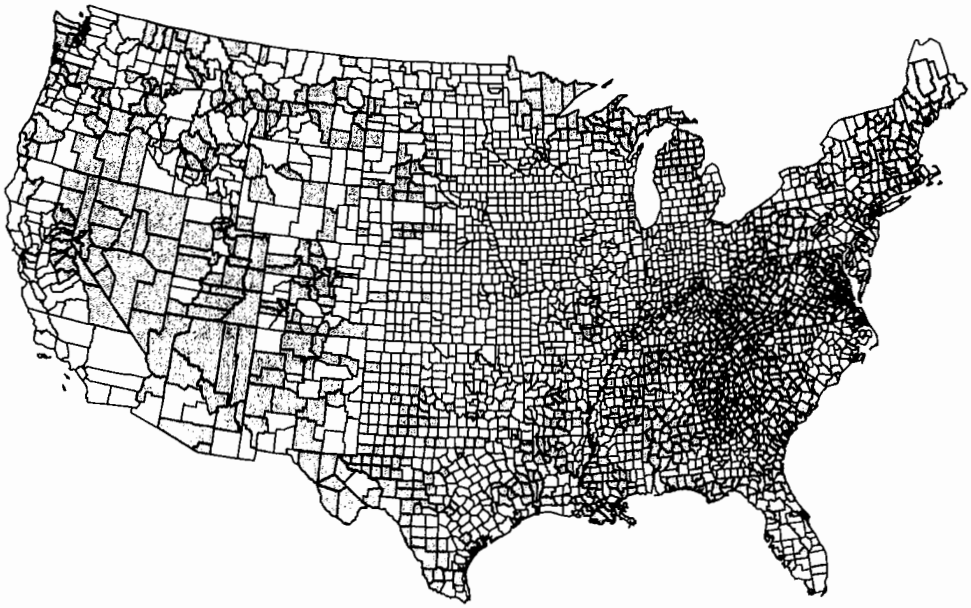
A county in the continental United States was considered noncompetitive if no banks meeting either of the aforementioned conditions were present in the county. The variable *NO_COMPETITION* was included in the model to identify counties with no banks or bank branches actively pursuing agricultural loans during at least one year of the study period. Using this criterion, less than one-half of all counties (1,436) would have been considered noncompetitive for the 1991 to 1993 period, and 1,565 for the 2001 to 2002 period. These counties were located in the more urbanized Northeast, Appalachia, Southeast, and Mountain states (Figure 2). The FCS is expected to have a higher market share of total farm lending in these noncompetitive counties.

As a result of higher risks and servicing costs, commercial banks tend to locate fewer banking offices in low-income areas (Avery et al., 1997). Consequently, potential farm borrowers located in low-income areas may face noncompetitive

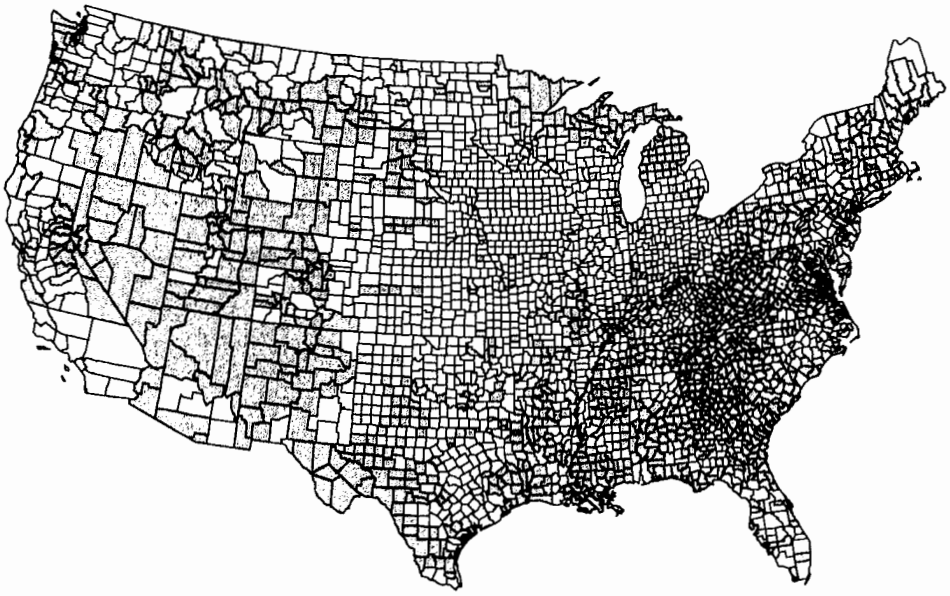
[10] Banks with over $500 million in total assets accounted for 39.2% of bank-held farm loans at mid-2002, up from 32.6% in four years.

[11] This 10% threshold is more lenient than the definitions of an agricultural bank used by the Federal Reserve or FDIC (USDA, 2003). The Federal Reserve and FDIC measures are intended to access an institution's safety and soundness, and not to characterize the competitiveness of markets which the institution serves.

[12] We selected three banks based on market concentration guidelines issued jointly by the U.S. Department of Justice and the Federal Trade Commission for use in horizontal merger and acquisition decisions.



**1991-1993**



**2001-2002**

**Figure 2. U.S. Regions (shaded areas) Where No Identifiable Commercial Bank Was Actively Pursuing Agricultural Loans, 1991–1993 and 2001–2002**

credit markets. To measure the effect of poor economic conditions on the probability of borrowing from the FCS or banks, a binary variable, *MED_HHI*, was included. The variable was given a value of 1 for counties where the median household income (as determined by the most recent *Census of Population*) was in the two lowest national quartiles (less than $32,000 for 1999 and $24,000 for 1989). Since the FCS is expected to serve all farmers in all regions with a basis for credit, low-income counties were considered more likely to fall within the FCS market segment.

In counties with fewer farm borrowers, farm loan demand may be insufficient for banks or other lenders to allocate resources toward agricultural lending. The share of the total county population comprised of farm residents (*FARM_SHR*) from the 1990 and 2000 *Census of Population* was used to measure agriculture's relative economic importance within a county. It was hypothesized that farm credit markets would be more competitive in counties where farmers are more numerous. Hence, new borrowers in counties where farmers were more common would be expected to fall within the bank market segment, while new borrowers within counties with fewer farmers would be more likely to fall within the FCS market segment.

## Organizational Variables

Banks and the FCS have different ownership, management, and organizational structures that affect their ability to tolerate and manage lending risk. A lender's ability to manage risk affects the underwriting standards applied to farm loans, and hence the segment of the credit markets served. It is difficult, however, to ascertain how organizational structure may affect the market segment served by the FCS and banks.

As full-service financial institutions, banks may have a much more diversified investment portfolio and thus may be less concerned about the relative risk associated with lending to agricultural enterprises than FCS lenders. But, this might not be true for small banks located in farm-dependent areas where nonfarm lending options are limited. Also, some banks may adopt more stringent underwriting standards toward farm lending due to a lack of knowledge of agricultural businesses. Greater use of FSA loan guarantee programs suggests banks may be using these programs to better manage the risks associated with lending to less creditworthy farmers (Dodson and Koenig, 1998).

As a consequence of the FCS's concentration in agricultural assets, its management may implement more conservative loan underwriting standards compared to those of banks. On the other hand, by specializing in agricultural loans, FCS managers may be more capable in identifying and managing farm credit risks, which could result in more aggressive lending standards. And, a better ability to diversify geographically may enable FCS to handle greater lending risk. The consolidation of FCS lenders this past decade increased their ability to mitigate lending risks through more extensive geographic diversification, while greater use of loan sales, loan participations, and Farmer Mac loan guarantees significantly improved credit risk management relative to the early-1990s study period.[13]

As farmer-owned cooperatives, FCS managers report to borrower owners, whereas bank managers report to investors. The different ownership structure is also likely to influence the relative loan portfolio composition of these two lender groups. Finally, relative to bank regulators, FCA examiners focus primarily on FCS institutions and are perhaps better acquainted with the risks and issues affecting agricultural lending. With the greater expertise and farm familiarity of FCA examiners, FCS lenders

[13] The number of FCS lending associations fell from 243 in 1993 to 110 in 2002.

may be better able to satisfy regulator concerns on higher risk farm loans.

To determine the extent to which organizational differences were affecting market segmentation, common loan underwriting standards for solvency, debt repayment capacity, and profitability were included in the model. Solvency was measured using the borrower's debt-to-asset ratio (*DA_RATIO*). The total outstanding debt and assets used to calculate the debt-to-asset ratio were restated to account for loans repaid during the year. Debt repayment capacity (*TDBTCOV*) was measured using the term debt coverage ratio and included nonfarm sources of income. Profitability (*ROA*) was measured using the return on assets for the farm business.

Capitalization or farm net worth was used to measure the ability of the farm to withstand economic downturns. Because larger net worth may be the result of larger farm size rather than better capitalization, capitalization was expressed as net worth divided by annual sales and grouped by quartiles (*LOW_CAP, 2ND_CAP, MED_CAP, HI_CAP*). A farm was considered financially vulnerable (*VULNERABLE*) if total household income was below the poverty level and the debt-to-asset ratio was greater than 0.40.

## Targeting Variables

To assure that presumed undeserved groups within society have access to credit, Congress has instituted policies requiring federal lenders and government-sponsored enterprises to target their lending resources to disadvantaged groups or economically distressed areas. Section 4.19 of the Farm Credit Act of 1971 specifically directs the FCS to adopt policies designed to increase its service to young, beginning, and small farmers (YBS). The FCA placed greater emphasis on enforcing this legislative mandate by ısuing a policy statement in 1998 which nnounced, "Each Board of Directors ıthin the System should renew its commitment to be a reliable, consistent, and constructive lender for YBS borrowers." While the FCS does not have quantifiable targeting goals like some other government-sponsored enterprises, the directive led to new public reporting requirements and greater YBS program development for reaching these groups (U.S. National Archives and Records Administrations, *Federal Register*, 2003).

Following FCA's definitions of young and beginning farmers, these farmer groups (*BEG_YOUNG*) were identified based on the number of years of farming experience and on the age of the operator. Farm Costs and Returns Survey (FCRS) data for 1991–1993 contained no information on the years of farming experience; therefore, the dependent variable for this period was based on age only. Because of these statutory requirements, it is expected that young and beginning farmers are more likely to fall within the FCS market segment.

Older farmers, those over age 55 (*OVER_55*), may have a greater need for a broad array of financial products and services, and hence might be expected to fall within the bank segment. On the other hand, older farmers on average have larger investments in farmland and are more inclined to utilize real estate financing over operating or chattel financing. Therefore, since the FCS has a competitive advantage relative to banks in providing mortgage credit, there was no expectation placed upon which lender groups these older borrowers might fall into.

While the FCS and banks have been prohibited from practicing discrimination in lending, there are no specific requirements for either lender group to target their lending to racial or ethnic minority farmers. Racial and ethnic minorities tend to be located in counties characterized by high poverty (Jolliffe, 2004). The economic deprivation characterizing regions where racial and ethic minorities are concentrated may discourage commercial banks from serving some of these regions. Since the FCS is

supposed to be a nationwide lender, it was expected that the FCS might have a greater likelihood of serving this market. The presence of racial and ethnic minority farmers (*RACE_ETHNIC*) was measured as the ratio of these farm residents to total farm residents in a county.[14]

## Data

The 2001–2002 Agricultural Resource Management Survey (ARMS) and the 1991–1993 Farm Costs and Returns Survey (FCRS) were used to obtain data on the characteristics of those receiving new loans from the FCS and banks.[15] The 2001–2002 ARMS data represented the most recently available data for this investigation. Both surveys provide detailed financial and demographic data for each new bank and FCS borrower.

The FCRS and ARMS are complex sample surveys comprised of data originating with sample designs that adjust for nonresponses and differing probabilities of selection. Complex samples differ from random surveys in that random surveys assume independence of observations, while complex surveys do not. Standard statistical techniques assume a random sample and result in under-representation of variances when analyzing data from complex surveys. Therefore, analysis of data from complex surveys should include specific calculation of variance estimates to account for these sample characteristics. Because the ARMS and FCRS utilized different survey designs, they consequently require different estimation techniques. For the ARMS, a delete-a-group jackknife approach with replication method was used, while SAS's "Surveyreg" procedure was used for the FCRS (Dubman, 2000).

The 1990 and 2000 *Census of Population* provided county-level demographic data on incomes, population, and racial and ethnic minority populations. The Federal Deposit Insurance Corporation's (FDIC's) summary of deposit data were combined with Federal Reserve call report data to estimate the geographic locations of bank branch offices likely to supply farm credit. FDIC summary of deposit data as of June 30, 1993 and June 30, 2002 were matched with corresponding call report data for 1993 and 2001–2002 to identify bank branches.

## Results

Mean value comparisons suggest substantial differences between market segments served by the FCS and banks. The FCS appears to have had a greater presence among full-time commercial-sized farms during both periods. New FCS borrowers operated larger farms, as indicated by the value of farm production, acres operated, and total farm assets (Tables 2 and 3). Compared to new bank borrowers, the household incomes of new FCS borrowers were more reliant on income from the farm business. Mean statistics also showed that FCS and bank borrowers have similar average debt-to-asset ratios and faced similar levels of financial stress. Over both periods, the share of new FCS loans made in noncompetitive counties was over twice the share of new bank loans made.

The multivariate logit analysis reveals that FCS and commercial banks serve different market segments. Results for two models are presented for the 2001–2002 data (Table 4). Model A utilizes parameter definitions which are comparable to definitions used for the 1991–1993 period. Model B incorporates additional information which was only available in the ARMS. Specifically, young and beginning farmers are uniquely identified as well as specific loan purposes.

[14] While ARMS provides farm-level information on race, ethnicity, and gender, there were too few observations of racial and ethnic minorities to yield statistically reliable estimates. Therefore, *Census of Population* data were used as a source of data on racial and ethnic minorities in farming.

[15] Since 1996, the ARMS has been USDA's primary survey instrument for obtaining data on a broad range of issues about agricultural resource uses and costs, and farm financial conditions. Prior to 1996, USDA's farm financial instrument was the FCRS. For more information on these surveys, see Mishra et al. (2002, Appendix A).

**Table 2. Financial and Structural Characteristics of Farms Acquiring Debt in 2001–2002, by Lender Group Providing the Majority of New Credit**

| Description | Primary Lender Group: FCS | Banks | All Other Lenders | *t*-Statistic FCS-Bank Difference |
|---|---|---|---|---|
| **Farm Characteristics:** | | | | |
| Total farm assets ($) | 1,016,774 | 665,721 | 648,761 | 3.83 |
| Total farm debt ($) | 230,565 | 170,333 | 150,292 | 1.94 |
| New farm debt ($) | 133,548 | 100,104 | 51,048 | 2.25 |
| Farm net worth ($) | 786,209 | 495,388 | 498,469 | 3.45 |
| Value of farm production ($) | 283,921 | 172,015 | 165,859 | 0.82 |
| Total household income ($) | 69,714 | 60,873 | 70,952 | 3.83 |
| Farm income to the household ($) | 28,073 | —[a] | 13,775 | 1.44 |
| Acres operated (no.) | 1,154 | 754 | 484 | 2.27 |
| Primary operator age (years) | 48.2 | 49.5 | 47.8 | 0.99 |
| **Independent Variables:**[b] | | — Ratio — | | |
| *DA_RATIO* | 0.29 | 0.30 | 0.37 | 0.04 |
| *TDBTCOV* | 0.88 | 0.74 | 1.28 | 0.37 |
| *OVER_55* | 0.24 | 0.28 | 0.23 | 1.75 |
| *BEG_YOUNG* | 0.26 | 0.22 | 0.28 | 0.37 |
| *FULLTIME* | 0.16 | 0.11 | 0.13 | 1.18 |
| *PARTTIME* | 0.30 | 0.38 | 0.33 | 1.15 |
| *HOBBY* | 0.30 | 0.30 | 0.33 | 0.02 |
| *MED_HHI* | 0.26 | 0.34 | 0.22 | 2.16 |
| *NO_COMPETITION* | 0.21 | 0.12 | 0.17 | 1.01 |
| *PURCH* | 0.47 | 0.38 | —[a] | 2.19 |
| | | — Percent — | | |
| *VULNERABLE* | 3.2 | 3.2 | 2.6 | 0.03 |
| *ROA* | 1.0 | -0.2 | -0.4 | 0.01 |
| *LOW_CAP* | 6.0 | 11.0 | 10.0 | 1.80 |
| *MED_CAP* | 46.0 | 40.0 | 41.0 | 1.52 |
| *HI_CAP* | 6.0 | 10.0 | 10.0 | 1.62 |
| *FARM_SHR* | 5.5 | 7.0 | 5.3 | 1.21 |
| *RACE_ETHNIC* | 5.4 | 4.7 | 5.2 | 0.92 |

*Source:* USDA's Agricultural Resource Management Survey (ARMS), 2001 and 2002.
[a] Insufficient data for disclosure.
[b] See Table 1 for detailed description of variables.

The log likelihood statistic was highly significant for both models, indicating that new FCS and bank borrowers were segmented by at least one of the attributes (Table 5). The Homer-Lemeshow test was not significant in any model, suggesting the model fit was adequate. As shown by the C-statistic, the model correctly classified about 65% of the observations. Also, ROC curves associated with each model had a slope of less than 45%, indicating each model had some predictive accuracy.

From Table 5, the sensitivity statistic represents the share of observations correctly predicted to be FCS borrowers, while specificity indicates the share correctly predicted to be bank borrowers. A priori probability levels, bank borrowers were correctly predicted in

**Table 3. Financial and Structural Characteristics of Farms Acquiring Debt in 1991–1993, by Lender Group Providing the Majority of New Credit**

| Description | Primary Lender Group: FCS | Banks | All Other Lenders | *t*-Statistic FCS-Bank Difference |
|---|---|---|---|---|
| **Farm Characteristics:** | | | | |
| Total farm assets ($) | 713,756 | 477,572 | 460,429 | 6.17 |
| Total farm debt ($) | 171,074 | 119,955 | 115,174 | 4.48 |
| New farm debt ($) | 81,989 | 54,684 | 48,763 | 4.19 |
| Farm net worth ($) | 542,682 | 357,618 | 345,256 | 5.83 |
| Value of farm production ($) | 200,432 | 143,710 | 108,857 | 2.92 |
| Total household income ($) | 48,421 | 38,881 | 42,642 | 2.14 |
| Farm income to the household ($) | 3,845 | 1,824 | 3,267 | 1.99 |
| Acres operated (no.) | 1,366 | 744 | 650 | 3.45 |
| Primary operator age (years) | 48.4 | 46.6 | 47.5 | 1.68 |
| **Independent Variables:** [a] | | — Ratio — | | |
| *DA_RATIO* | 0.24 | 0.25 | 0.25 | 0.86 |
| *TDBTCOV* | 2.00 | 1.80 | 2.09 | 1.16 |
| *OVER_55* | 0.28 | 0.26 | 0.23 | 0.53 |
| *YOUNG* | 0.17 | 0.24 | 0.23 | 1.77 |
| *FULLTIME* | 0.21 | 0.11 | 0.10 | 3.79 |
| *PARTTIME* | 0.23 | 0.31 | 0.29 | 2.41 |
| *HOBBY* | 0.21 | 0.29 | 0.37 | 2.10 |
| *MED_HHI* | 0.25 | 0.30 | 0.29 | 1.33 |
| *NO_COMPETITION* | 0.15 | 0.09 | 0.14 | 2.49 |
| | | — Percent — | | |
| *VULNERABLE* | 5.79 | 7.27 | 6.08 | 1.02 |
| *ROA* | 1.58 | 0.41 | -0.49 | 1.51 |
| *LOW_CAP* | 1.50 | 1.9 | 7.0 | 0.86 |
| *MED_CAP* | 48.0 | 41.1 | 24.6 | 0.96 |
| *HI_CAP* | 14.7 | 31.3 | 40.1 | 2.95 |
| *FARM_SHR* | 7.18 | 9.79 | 7.87 | 4.68 |
| *RACE_ETHNIC* | 2.74 | 2.46 | 3.88 | 0.27 |

*Source:* USDA's Farm Cost and Returns Survey (FCRS), 1991–1993.
[a] See Table 1 for detailed description of variables.

about two-thirds of the cases for 2001–2002, and in 59% of the cases for 1991–1993. Sensitivity results show that the model correctly classified FCS borrowers 60% of the time for the 1991–1993 period and 57% of the time for the 2001–2002 period. None of the eigenvalue condition indexes was greater than 10, suggesting collinearity had no impact on regression estimates (Belsey, Kuh, and Welsch, 2005).

Logistic regression results confirm previous studies showing FCS lenders serving larger farming operations. Parameter results for the *PARTTIME* and *HOBBY* variables were statistically significant with their signs indicating that these market segments were more likely to be served by banks (Table 4). The parameter results for *FULLTIME* commercial farmers were also as expected, though only statistically significant at the

**Table 4. Multivariate Logit Model Analyzing Loans Made by the FCS and Banks: Model Estimates and Standard Errors (in parentheses)**

| | | | 2001–2002 | | | |
|---|---|---|---|---|---|---|
| **Variable** | **1991–1993** | ***p*-Value** | **Model A** | ***p*-Value** | **Model B** | ***p*-Value** |
| Intercept | -1.13214<br>(0.2933) | 0.000 | -1.6303<br>(0.30121) | 0.0104 | -1.7599<br>(0.30126) | 0.010 |
| *FULLTIME* | 0.43391<br>(0.1930) | 0.025 | 0.43848<br>(0.3876) | 0.129 | 0.41350<br>(0.4125) | 0.158 |
| *PARTTIME* | -0.60478<br>(0.2470) | 0.014 | -1.04072<br>(0.5949) | 0.040 | -1.03074<br>(0.6595) | 0.059 |
| *HOBBY* | -0.77630<br>(0.2817) | 0.006 | -0.61906<br>(0.3093) | 0.023 | -0.62152<br>(0.3329) | 0.031 |
| *NO_COMPETITION* | 0.50341<br>(0.2463) | 0.041 | 0.91876<br>(0.5019) | 0.034 | 0.90096<br>(0.5618) | 0.054 |
| *FARM_SHR* | -0.52026<br>(0.1460) | 0.000 | -1.10008<br>(1.9608) | 0.287 | -1.00741<br>(1.9571) | 0.303 |
| *MED_HHI* | -0.00731<br>(0.2235) | 0.974 | 0.09384<br>(0.1910) | 0.312 | 0.13479<br>(0.2146) | 0.265 |
| *DA_RATIO* | -0.25510<br>(0.4217) | 0.545 | 0.00062<br>(0.1097) | 0.498 | 0.00000<br>(0.1026) | 0.500 |
| *TDBTCOV* | 0.03891<br>(0.0383) | 0.310 | 0.02154<br>(0.0530) | 0.342 | 0.00234<br>(0.0556) | 0.483 |
| *VULNERABLE* | -0.04368<br>(0.3036) | 0.886 | -0.14620<br>(0.4556) | 0.374 | -0.12627<br>(0.4577) | 0.391 |
| *ROA* | 0.69315<br>(2.5561) | 0.786 | 0.50213<br>(1.8674) | 0.394 | 0.98184<br>(1.7916) | 0.292 |
| *LOW_CAP* | -0.38415<br>(0.5059) | 0.448 | -0.57777<br>(1.0957) | 0.299 | -0.58116<br>(1.1107) | 0.300 |
| *MED_CAP* | 0.32321<br>(0.2047) | 0.115 | 0.36076<br>(0.3679) | 0.163 | 0.33056<br>(0.4261) | 0.219 |
| *HI_CAP* | -0.38661<br>(0.5063) | 0.445 | -0.56218<br>(0.6455) | 0.192 | -0.62977<br>(0.6581) | 0.169 |
| *OVER_55* | -0.08687<br>(0.2198) | 0.693 | -0.07058<br>(0.2168) | 0.372 | -0.08990<br>(0.2214) | 0.342 |
| *YOUNG* | -0.29119<br>(0.2379) | 0.221 | 0.37140<br>(0.5457) | 0.248 | | |
| *BEG_YOUNG* | | | | | 0.13248<br>(0.5605) | 0.407 |
| *RACE_ETHNIC* | -0.93298<br>(1.2677) | 0.462 | 0.14637<br>(0.8549) | 0.432 | 0.18549<br>(0.9641) | 0.424 |
| *PURCH* | | | | | 0.46540<br>(0.1834) | 0.006 |

*Notes:* Model A for 2001–2002 utilized parameters which correspond to variables in 1991–1993. Model B incorporates additional information available in 2001–2002.

**Table 5. Summary Statistics for Multivariate Logit Model Analyzing Loans Made by the FCS and Banks**

| Statistic | 1991–1993 | 2001–2002 Model A | 2001–2002 Model B |
|---|---|---|---|
| Expected probability of borrowing from FCS | 0.142 | 0.138 | 0.138 |
| Log likelihood ratio | 370,622 | 25,214 | 30,768 |
| Degrees of freedom (sample) | 3,228 | 3,262 | 3,262 |
| Level of significance | > 0.0001 | > 0.0001 | > 0.0001 |
| Model Assessment: | | | |
| Specificity [a] | 59.0 | 62.7 | 62.0 |
| Sensitivity | 60.0 | 56.5 | 56.6 |
| Rescaled $R^2$ | 0.06 | 0.067 | 0.071 |
| Homer-Lemeshow | 0.4311 | 0.5142 | 0.1942 |
| *C*-Statistic | 0.647 | 0.631 | 0.652 |

[a] Specificity uses a probability level for FCS of 0.142 for 1991–1993, and 0.138 for 2001–2002.

5% level for the 1991–1993 period. The 2001–2002 *FULLTIME* commercial farmer parameter results were statistically significant at only the 13% level for model A and at the 16% level for model B. Estimation of standard errors in complex surveys is sensitive to the estimation procedure employed which, in turn, will influence tests of significance (Dubman, 2000). For the *FULLTIME* variable, the parameter estimate varied little between time periods, while the standard error increased. But, differences in levels of significance between time periods may simply reflect the different estimation procedures rather than changes in the underlying economic variables. Thus, in comparing results for the different time periods, greater consideration is given to relative impacts on the probability of borrowing from the FCS or banks.[16]

The odds ratios indicate that full-time commercial-size farms were 1.55 times more likely to be FCS borrowers during the 2001–2002 period, and 1.34 times in 1991–1993 (Table 6). Part-time farms were half as likely to borrow from the FCS as from banks in 1991–1993, and only 35% as likely in 2001–2002. Hobby farmers were 61% as likely to borrow from the FCS in 1991–1993, and 54% as likely in 2001–2002.[17]

Parameter estimates for the *FULLTIME*, *PARTTIME*, and *HOBBY* variables did not significantly change between the time periods, suggesting little change in the effect of FCS and commercial bank lending policies despite ongoing structural and regulatory changes. For 2001–2002, the parameter measuring the share of total new loans used to fund purchases of real estate or equipment was positive and significant, indicating the FCS is more likely to serve borrowers using loans to fund new purchases.

The parameter sign for the *NO_COMPETITION* variable was positive, as expected, and significant for 1991–1993 suggesting that when few bank branches are present in a county, borrowers are

[16] The standard errors for variables obtained through a complex survey design are affected by the particular resampling method chosen. The delete-a-group jackknife procedure was selected because it has been the most commonly used for ARMS data. An alternative resampling method could have provided different standard errors, and consequently different inferences. Thus, in addition to the standard parameter significance, we looked at changes in parameter estimates over time and the sensitivity of results to changes in the independent variables.

[17] The model was re-estimated with the *FAMFARM* variable being substituted for *PARTTIME*. These results suggested family-size farms were just as likely to be FCS borrowers as bank borrowers during both time periods examined here.

more likely to obtain credit from the FCS. Similarly, *FARM_SHR* was significant and negative, indicating that farms located in counties with more farmers were more likely to borrow from banks. The odds ratios suggest farmers located in less competitive counties were 2.5 times more likely to be FCS borrowers in 2001–2002, and 1.78 times as likely to be FCS borrowers in 1991–1993.

Re-estimating the model by substituting a variable identifying highly competitive counties (*COMPETITIVE*) rather than noncompetitive counties revealed that farmers in counties considered highly competitive were only 0.77 times as likely to borrow from the FCS in 2001–2002, compared to 0.67 for 1991–1993 (Table 6). Though this finding points to an increase in importance of FCS lenders as a source of credit in less competitive counties from 1991–1993 until 2001–2002, one cannot conclude the difference to be statistically significant.

Regardless of the time period, the results suggest the FCS and banks were using similar underwriting standards to select borrowers. Most of the underwriting variables were statistically significant for either the 1991–1993 or the 2001–2002 periods. Furthermore, a 1% increase in the loan underwriting financial variables had essentially no impact on the probability of borrowing from the FCS relative to banks. There were indications that the FCS may be more averse to serving financially stressed farms. In 2001–2002, a financially vulnerable farm (*VULNERABLE*) was 0.86 times as likely to borrow from the FCS, compared to 1.09 for 1991–1993 (Table 6). The improvement in the financial position of FCS borrowers may reflect the overall improvement in the farm economy in the aftermath of the 1980s farm financial crises.

Farms with high amounts of net worth per dollar of sales and low amounts of net worth per dollar of sales were less likely to borrow from FCS. The log-odds ratio indicates that farms with intermediate amounts of net worth per dollar of sales

**Table 6. Sensitivity of Predicted Probabilities to Changes in Parameter Values**

| | Odds Ratio [a] | |
|---|---|---|
| **Variable** | **1991–1993** | **2001–2002** [b] |
| *FULLTIME* | 1.343 | 1.550 |
| *PARTTIME* | 0.510 | 0.353 |
| *HOBBY* | 0.607 | 0.538 |
| *NO_COMPETITION* | 1.789 | 2.506 |
| *COMPETITIVE* [c] | 0.670 | 0.766 |
| *MED_HHI* | 0.931 | 1.098 |
| *VULNERABLE* | 1.087 | 0.864 |
| *YOUNG* | 1.024 | 1.453 |
| *BEG_YOUNG* | N/A | 1.142 |
| *OVER_55* | 1.170 | 0.927 |
| *LOW_CAP* | 0.567 | 0.561 |
| *MED_CAP* | 1.244 | 1.434 |
| *HI_CAP* | 0.684 | 0.570 |
| *PURCH* [d] | N/A | 1.593 |
| | **– % Change in Prob. –** [e] | |
| *DA_RATIO* | -0.117 | -0.03 |
| *FARM_SHR* | -0.317 | -0.06 |
| *TDBTCOV* | 0.097 | 0.02 |
| *ROA* | 0.01 | 0.01 |
| *RACE_ETHNIC* | -0.03 | -0.00 |

[a] Change in probability of a farmer being included in FCS market segment as a result of an independent variable having a value of 1.
[b] Estimates are calculated from Model A or B values, depending on availability.
[c] Results from model which substituted counties considered highly competitive with respect to farm loans for the *NO_COMPETITION* variable.
[d] Calculated as log-odds of being an FCS borrower based on 100% of loan funds used to fund new purchases versus 0% used to fund new purchases. (Variable was not available for the 1991–1993 period.)
[e] For continuous variable, sensitivity was measured as the change in probability of farmer being included in the FCS market segment as a result of a 1% change in the independent variable.

(*MED_CAP*) were 1.24 times as likely to borrow from FCS in 1991–1993, and 1.43 times as likely to borrow from FCS in 2001–2002. Such results are consistent with FCS regulatory guidelines stating credit should be provided to full-time bona fide farmers and ranchers to the extent of their creditworthiness. Farms with low net worth per dollar of sales are likely to be less creditworthy, while large amounts of capital per dollar of sales may be more

characteristic of part-time or hobby farmers. Thus, the larger average net worth of FCS borrowers, relative to bank borrowers, may simply reflect their larger average farm size rather than suggesting that FCS lenders tend to serve wealthier farmers.

The odds ratio indicates that young farmers were 1.45 times more likely to be new FCS borrowers than new bank borrowers during the 2001–2002 period (Table 6). This represents a sizable rise from the odds ratio of 1.02 calculated for 1991–1993. Also, differences in the parameter estimates between the time periods could be considered statistically significant at the 15% level—implying FCA's 1998 policy change with respect to YBS lending rules may have had at least some impact on FCS lending activity to these groups.

The results for the presence of racial or ethnic minorities (*RACE_ETHNIC*) in a county did not identify this as a significant factor in market segmentation. However, racial and ethnic minorities are geographically concentrated, with many large farming regions having few racial or ethnic minorities present. Separate logistic regressions were run which incorporated a binary variable for counties with a higher than average percentage of racial and ethnic minorities. Though not reported here, these results showed that farms in these racial minority counties were only 0.6 times as likely to be FCS borrowers as opposed to bank borrowers. This suggests a possible need for further research of the relationship between borrower race and ethnicity and credit market segmentation.

## Summary and Conclusions

In general, the model results are consistent with the expectation that the Farm Credit System and commercial banks are serving somewhat different segments of the farm credit market. As expected, full-time commercial-sized farms incurring debt in 2001 and 2002 were more likely to borrow from the FCS, while part-time and hobby farms were more likely to borrow from banks. Such results are consistent with federal regulations governing the FCS lending policy that directs the government-sponsored enterprise to provide "full credit to full-time bona fide farmers" and "conservative credit to part-time farmers."

The model's results may simply reflect the comparative advantages of the two dominant farm lender groups. The specialized farm financial services of the FCS, such as farm credit and leasing products, may be more economically beneficial to full-time farmers than to part-time or hobby farmers. And the broader array of financial services provided by banks may be more economically beneficial to part-time and hobby farmers. Even with its funding advantages, which are greatest for long duration credits, FCS lenders may find it more difficult to recoup fixed lending costs and remain competitive with full-service banks when farm credit requests are small or infrequent.

The results indicate there is no discernable difference between bank and FCS underwriting standards. Earlier studies had suggested that FCS borrowers were more highly capitalized when compared to bank customers. However, based on results of this analysis, this finding merely reflects the larger average farm size of FCS borrowers.

Results also indicate that farms in counties with fewer agricultural banks or fewer farmers were more likely to use FCS lenders. This finding is consistent with the FCS's statutory mission that it serves all bona fide farmers with a basis for credit, regardless of geographic location. It also suggests that the presence of the FCS is more important to areas where farm credit markets may be less competitive. Though these less competitive counties comprised about half of all U.S. counties, they represent only a small share of U.S. farm production. Only about 15% of farms originating new

loans over each time period were located in counties defined as less competitive.

In contrast to the results reported in some earlier studies, the FCS was found to be a more likely supplier of credit to young and beginning farmers than commercial banks. This level of FCS lending to this market segment might be the result of recent Farm Credit Administration policy initiatives to bolster system-wide lending to these targeted groups. FCS's greater propensity to serve young and beginning farmers and farmers facing less competitive credit markets points to a somewhat diminished need for subsidized federal credit programs, at least with respect to these groups.

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