JULY 2004 R.B. 2004-09

Agricultural Finance Markets in Transition

Proceedings of
The Annual Meeting of NCT-194

Hosted by the Center for the Study of Rural America,
Federal Reserve Bank of Kansas City

October 6 - 7, 2003

Edited by
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Publication Price Per Copy: $12.00

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Preface

The meetings of NCT-194 were held in Kansas City, Missouri on October 6-7, 2003. The Center for the Study of Rural America at the Federal Reserve Bank of Kansas City served as the host institution. NCT-194 was formed at the expiration of NC-221 and before the approval of NC-1014. The purpose of the group was to conduct multi-state research on transitioning agricultural finance markets and to develop a proposal for a new multi-state research committee.

This publication contains the agenda and minutes from our meeting as well as the majority of the selected papers that were presented at the meeting. The annual meeting consisted of several sessions of selected research papers that reported on current research efforts as well as sessions designed to facilitate the development of the proposal for our new multi-state research project. I am happy to report that the project has been approved as NC-1014, Agricultural Finance Markets in Transition.

The executive committee consisted of Chair Matthew Diersen, Vice-Chair Brent Gloy, and Secretary Timothy Park. This committee selected the papers for presentation and organized the meetings. The group would like to thank Jason Henderson for his assistance in developing the agenda for the meeting as well as making arrangements to host the group. We would also like to thank invited speakers Mark Drabenstott, Ross Anderson, Gary Mazour, Don Macke, and David McGranahan for sharing their time and thoughts with the group.

Brent Gloy
Vice-Chair 2002-2003

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AGENDA

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8:15 – 9:00 Welcome and presentation on Major Challenges in Rural America, Mark Drabenstott, Vice President and Director, Center for the Study of Rural America, Federal Reserve Bank of Kansas City

9:00 – 10:00 Ross Anderson, Vice President of Credit, Agribank and member of FCS President's Commission on Credit Risk: FCS approaches to assess, monitor, and manage credit risk

10:00 – 10:20 Break

10:20 – 11:20 Approaches to Evaluating Credit Risk

A. Issues in Credit Risk Assessment in Agricultural Credit Markets, R. Onyeaghala and P. Ellinger
B. Credit Risk Models: An Application to Agricultural Lending, A. Katchova and P Barry
C. Adapting Credit Risk Models to Agriculture, L. Zech and G. Pederson

11:20 – 12:00 A Multi-State Approach to Assessing the Potential of Farm Savings Accounts

A. Overview of Alternative Farm Savings Account Programs and Multi-state Efforts to Evaluate Alternative Farm Savings Account Programs, B. Gloy, et al.
B. Results from Analyses of the Viability of and Benefits from Farm Savings Accounts for New York and Illinois, P. Ellinger, et al.

12:00 – 1:00 Lunch

1:00 – 1:50 The Intersection of Rural Communities and Finance: Research Needs and Opportunities in Rural America; Don Macke, Co-Director, Center for Rural Entrepreneurship; David McGranahan, Economic Research Service

1:50 – 2:50 Rural Economy: Farm Policy and Finance

A. The Impact of the Conservation Reserve Program on Farm Service and Recreation Establishments and Jobs, P. Sullivan, D. McGranahan, and C. Hallahan
B. Rural Small Business Finance: Evidence from the 1998 Survey of Small Business, C. Gustafson
C. Credit Counseling and Mortgage Termination by Low-Income Households: Evidence from a Mulit-State Counseling Program, V. Hartarska and C. Gonzalez-Vega

2:50 – 3:00 Break

3:00 – 4:00 Farm Revenue Risk and Financial Institution Efficiency

A. Relationships among the Counter-Cyclical Program, Crop Revenue, and Crop Insurance Payments, B. Sherrick, R. Hauser, and G. Schnitkey
B. Risk Sharing and Incentives under Crop Insurance and External Equity Financing, S. Seo, D. Leatham, and P. Mitchell
C. Input Efficiency in Commercial Banks: A Normalized Quadratic Input Distance System, T. Marsh, A. Featherstone, and T. Garrett

4:00 – 4:10 Break

4:10 – 4:50   Credit Use and Availability

A. Analysis of Borrower and Lender Use of Interest Assistance on FSA Guranteed Farm Loans, B. Ahrendsen, et al.
B. An Analysis of Market Segmentation in Farm Credit Markets, S. Koenig, C. Dodson, and J. Ryan.

Tuesday, October 7th

8:00 – 8:30 Business meeting and comments for administrative adviser

8:30 – 9:15 Break into groups to develop work plans and projects for each of the four proposed objectives:

A. Determine the effects of changes in international competitive balance and federal and state policies affecting agriculture on the financial and economic performance of farms, agribusinesses and rural financial markets
B. Determine the effects of market, policy, and structural change in the agricultural and financial market sectors on the financial soundness, safety, and management of financial institutions that supply financial capital to agriculture
C. Evaluate the management strategies, capital needs, and financial performance required for the long-term sustainability of firms in the food and agribusiness sector
D. Final objective (currently under development and will likely include examining issues related to rural community development and finance)

9:15 – 10:00 Reports from groups on specific project ideas. Allow time for members to agree to participate in objectives whose breakout groups they did not attend.

10:00 – 10:15 Break

10:15 – 11:15 Financial Structure and Financial Management

A. The DuPont Profitability Analysis Model: An E-Learning Application and Evaluation, J. Melvin and M. Boehlje, C. Dobbins, A. Gray
B. Sustainable Growth Trends in U.S. Agriculture, C. Turvey and C. Escalante
C. Off-farm Income and Demand for Farm Capital Investment, C. Lagerkvist, H. Andersson, M. Campos, and K. Olson

11:15 – 12:00 Topics in Agricultural Finance

A. Evaluating USDA Forecasts of Farm Assets, T. Covey and K. Erickson
B. How Large is the Competitive Edge that U.S.-Based Futures Provide to U.S. Farmers? S. Lence

MINUTES

Minutes of NCT-194 [NC221]
Agricultural Finance Markets In Transition
Covering: October 2002 – September 2003
Annual Meeting: October 6-7, 2003

Administrative Advisor:
Dr. Eric Hoiberg
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South Dakota State University
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Vice-Chair:
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Secretary:
Dr. Timothy Park
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Participants:

Peter Barry (University of Illinois), Ted Covey (Economic Research Service), Matt Diersen (South Dakota State University), Wayne Diveley (Federal Reserve Bank of Kansas City), Mark Drabenstott (Center for the Study of Rural America), Paul Ellinger (University of Illinois), Allen Featherstone (Kansas State University), Walter Gardiner (Farm Credit Administration), Brent Gloy (Cornell University), Cole Gustafson (North Dakota State University), Valentina Hartarksa (Auburn University), Jason Henderson (Center for the Study of Rural America), Eric Hoiberg (Iowa State University), Larry Janssen (South Dakota State University), Ani Katchova (University of Illinois), Juno Kim (Texas A&M University), Steve Koenig (Economic Research Service), Eddy L. LaDue (Cornell University), Carl Lagerkvist (Swedish University of Agricultural Sciences), Sergio Lence (Iowa State University), Zech Lyubov (University of Minnesota), David McGranahan (Economic Research Service), Don Macke (RUPRI), Tom Marsh (Kansas State University), Charles Moss (University of Florida), Raphael Onyeaghala (Southwest Minnesota State University), Timothy Park (University of Georgia), Glenn Pederson (University of Minnesota), Jill Phillips (University of Illinois), Lindon Robison (Michigan State University), Sangtaek Seo (Texas A&M University), Bruce Sherrick (University of Illinois), Patrick Sullivan (Economic Research Service), Chris Taggart (Federal Reserve Bank of Kansas City), Calum G. Turvey (Rutgers University), Stanton Ullerich (Buena Vista University), Christine Wilson (Purdue University).

Annual Meeting Minutes
October 6-7, 2003

The 2003 Annual Meeting of NCT-194 [NC221] was held October 6 and 7 in Kansas City, Missouri at the headquarters of the Federal Reserve Bank of Kansas City. The meeting was called to order at 8:00 A.M. on October 6 by Vice-Chairman Brent Gloy. The first two items were presentations by experts in rural and regional economic development trends from the Center for the Study of Rural America and a financial analyst from Farm Credit Services. A joint presentation on major challenges facing rural America by Mark Drabenstott, Vice President and Director and Jason Henderson, both of the Center for the Study or Rural America, Federal Reserve Bank of Kansas City initiated the sessions. Mark Drabenstott discussed strategies for the new economy which revolve around an emphasis on reinventing regions by building regional partnerships, identifying a unique competitive niche, and enriching a region’s supply of equity capital. Jason Henderson highlighted how the economic transformation of rural

America is influenced by the role of technology and the demand for recreation amenities and the emerging importance of service based industries as an economic cornerstone for these communities. Rural communities are beginning to capture high-skill service industries and high-wage jobs by building on the quality of recreational and lifestyle amenities these areas possess and by upgrading the skill level of local businesses and the labor force.

Gary Mazour, Vice President of Credit for Farm Credit Services of America delivered a presentation on credit risk management focusing on the disclosure of information for assessing credit quality. Special emphasis was placed on emerging issues in the risk rating system and criteria for developing tools to assist in growing and managing the total loan portfolio. Ongoing research and scenario development on how to develop uniform methods to assess risk within and among institutions in the farm credit system were highlighted. A primary objective is to establish a risk rating model that complies with the guidelines in the Basel II and to establish definitions and objective criteria that are highly predictive over the business cycle.

The participants spent the rest of the morning and afternoon in 6 sessions of selected papers. The papers presented in these sessions addressed the objectives of NCT-194 [NC221] and were the products of the work of NC-221 members along with invited participants from government research groups and regional planning and development centers. A total of 15 papers were presented in the sessions. Nearly all of the papers were the product of several multi-state, multi-institution collaborations. An interactive presentation featured a cross disciplinary discussion between rural sociology perspectives and business entrepreneur viewpoints on the role of finance and capital in retaining and growing rural entrepreneurs and stimulating rural community growth.

The papers were grouped into sessions according to subject matter and involved participants in the project along with invited experts from research centers, rural sociologists from the Economic Research Service, and advanced graduate students. The first session addressed the general area of competing approaches to evaluating credit risk. The research presented during the second selected paper session examined multi-state approaches that assess the viability of farm savings accounts. In the third session, two discussants outlined disciplinary approaches for defining and addressing the research needs for identifying and stimulating entrepreneurial opportunities in rural areas. The specific topics covered by these papers included:

Issues in Credit Risk Assessment in Agricultural Credit Markets
Credit Risk Models: An Application to Agricultural Lending
Adapting Credit Risk Models to Agriculture

A Multi-State Approach to Assessing the Potential of Farm Savings Accounts
Multi-state Efforts to Evaluate Alternative Farm Savings Account Programs
Analyses of the Viability of and Benefits from Farm Savings Accounts: New York and Illinois

The Intersection of Rural Communities and Finance: Research Needs and Opportunities
Discussants: Don Macke, Co-Director, Center for Rural Entrepreneurship
David McGranahan, Economic Research Service

Rural Economy: Farm Policy and Finance
The Impact of the Conservation Reserve Program on Farm Service and Recreation Establishments and Jobs
Rural Small Business Finance: Evidence from the 1998 Survey of Small Business
Credit Counseling and Mortgage Termination by Low-Income Households

Farm Revenue Risk and Financial Institution Efficiency
Relationships among the Counter-Cyclical Program, Crop Revenue, and Crop Insurance Payments
Risk Sharing and Incentives under Crop Insurance and External Equity Financing
Input Efficiency in Commercial Banks: A Normalized Quadratic Input Distance System

Credit Use and Availability
Analysis of Borrower and Lender Use of Interest Assistance on FSA Guaranteed Farm Loans
An Analysis of Market Segmentation in Farm Credit Markets

On the second day of meeting the project adviser Dr. Eric Hoiberg reviewed the process that must be followed to revise the project for reauthorization and the reporting guidelines for completing the current project. Members were informed that the new NIMSS system must be used to submit the new proposal. Dr. Hoiberg also told that group that a proposal must include a statement of issues, justification, and objectives. In addition, a successful proposal should include a discussion of the methods, milestones, outreach, organization, and governance. Dr. Hoiberg encouraged the group to consider how they might broaden the scope or focus of the project and suggested incorporating alternative disciplinary approaches in specific objectives of the project. Participants reviewed progress during the past year in integrating multidisciplinary perspectives into the project and outlined goals for additional outreach efforts.

The participants adjourned to small group sessions to develop work plans and projects to align with each of the four proposed objectives. The objectives are directed at the following areas of emphasis:

(1) determine the effects of changes in international competitive balance and federal and state policies affecting agriculture on the financial and economic performance of farms, agribusinesses and rural financial markets

(2) determine the effects of market, policy, and structural change in the agricultural and financial market sectors on the financial soundness, safety, and management of financial institutions that supply financial capital to agriculture

(3) evaluate the management strategies, capital needs, and financial performance required for the long-term sustainability of firms in the food and agribusiness sector

(4) develop linkages between emerging issues in rural finance and development and the role of social capital and rural entrepreneurship. The plan is to develop a diverse cross state research initiative to measure the impact of social capital on the economic development and performance of agricultural and rural communities.

Participants discussed current and ongoing research and presentation outlets related to the project. Charles Moss circulated for review a copy of the recently published book **Government Policy and Farmland Markets** (Iowa State Press, 2003) which incorporated research from project participants on a range of topic related to farmland values, government policies, capital markets and the role of urbanization, environmental quality, and rural amenities in farmland markets. The book is a timely and comprehensive look at farmland values oriented to a broad audience of government policy makers, lenders, agricultural economists, and decision makers in agribusiness.

Lindon Robison reported on emerging interdisciplinary contacts with other disciplines which can provide new perspectives for the analysis of rural finance issues. In the summer of 2003, eight past presidents of the American Agricultural Economic Association (AAEA) and the Rural Sociological Society (RSS) met in a mini-summit to discuss how to best benefit from the joint meetings of their respective associations. They agreed and supported the idea of using the social capital paradigm to bridge across the two disciplines and proposed papers for the Montreal joint meetings between the AAEA, RSS, and the

Canadian Agricultural Economics Association (CAES) to illustrate this bridge. Principal paper sessions from the meetings included cross disciplinary presentations on social capital and a symposium on the productive areas of common ground between agricultural economists and rural sociologists. The project recognized the value of interdisciplinary approaches and is working to incorporate the implications of social capital into the revised project.

A principal paper session proposal will be prepared for the summer meetings of the American Agricultural Economics Association in Denver, Colorado. The session proposal will follow up on the ideas developed from these meetings on issues in agri-finance and social capital and would include three papers and one discussant. The first paper proposes to use multi-state data to examine if social capital developed by low-income borrowers through their church associations improves repayment of loans provided through partnerships with community church leaders. The second paper will examine if social capital can explain the lower rate of rural bank consolidations than their urban counterparts. Finally, the third paper assesses whether lower rates of return on farmland can be explained by attachment values. Contacts with the newly formed Institutional and Behavioral Economics section will be initiated to secure their endorsement of the proposed principal paper session and to develop expanded linkages for future project work.

The papers for the second day were grouped into two sessions. These sessions presented the work of 7 authors and include collaborative work on off-farm income with a visiting professor from the Swedish University of Agricultural Sciences. The first session addressed issues in financial structure and financial management. The second set of papers examined current issues in agricultural finance.

Financial Structure and Financial Management
Sustainable Growth Trends in U.S. Agriculture
Off-farm Income and Demand for Farm Capital Investment

Topics in Agricultural Finance
Evaluating USDA Forecasts of Farm Assets
How Large is the Competitive Edge that U.S.-Based Futures Provide to U.S. Farmers?

Date and Location of Next Year's Meeting

The current chair will appoint a committee to determine a suitable location for the 2004 meeting and consult with the committee in identifying a set of locations for the meeting. Tentative plans are that the meeting will be held on October 4-5, 2004.

Current and Future Officers

The nomination committee plans to present nominations to the group for a new chairman, vice-chairman, and secretary with elections to be held in early 2004.

Submitted by**:**

Timothy Park
NC-221 Secretary

Credit Risk Models: An Application to Agricultural Lending

Ani L. Katchova and Peter J. Barry*

Abstract

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

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

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* Ani L. Katchova is an assistant professor and Peter J. Barry is a professor in the Department of Agricultural and Consumer Economics at the University of Illinois at Urbana-Champaign. The authors would like to thank Paul Ellinger and Dale Lattz for their helpful comments and suggestions.

Credit Risk Models: An Application to Agricultural Lending

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

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

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

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

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

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

Theoretical Models

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

Merton's Model

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

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

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

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

$$(2) \qquad PD_{it} = \Pr\left[A_{it} \le D_{it}\right].$$

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

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

where

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

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

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

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

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

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

Credit Risk and Capital Requirements Calculation

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

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

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

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

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

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

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

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

The standard deviation of default for a portfolio of farms is

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

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

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

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

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

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

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

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

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

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

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

Asset Return Correlation Model

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

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

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

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

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

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

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

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

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

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

Two Applied Credit Risk Models

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

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

The CreditMetrics Model

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

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

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

The KMV Model

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

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

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

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

Data

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

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

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

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

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

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

Results for the Portfolio of All Farms

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

Sensitivity Analyses

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

Definition of Default

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

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

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

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

Distribution of Farms in the Portfolio

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

Correlation

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

Results for the CreditMetrics and KMV Models

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

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

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

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

Summary and Conclusions

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

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

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

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

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

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Table 1. Descriptive Statistics

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

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

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

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

Notes: [a] Losses are expressed as a percent of the total debt in the portfolio and as a dollar value per farm.
[b] The unexpected losses will exceed UL(α) with a probability α.
[c] Value-at-Risk (VaR) is the sum of expected and unexpected losses. The VaR(1-α) represents the total capital needed to protect against both expected and unexpected losses at a (1- α) solvency rate.

Table 3. Sensitivity Analyses

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

Notes: [a] The basic model is the same as the model using the historical default rate in table 2.
[b] Losses are expressed as a percent of the total debt in the portfolio and as a dollar value per farm.
[c] The unexpected losses will exceed UL(α) with a probability α.
[d] Value-at-Risk (VaR) is the sum of expected and unexpected losses. The VaR(1-α) represents the total capital needed to protect against both expected and unexpected losses at a (1- α) solvency rate.

Table 4. Credit Score Migration Matrix (Used in the CreditMetrics Model) [a, b]

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

Notes: [a] Classes are defined based on credit score values.
[b] The migration matrix shows the probabilities of migrating from class *i* in year *t* to class *j* or default in year (*t*+1).

Table 5. The CreditMetrics Model

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

Notes: [a] Each farm is assigned into a class based on the value of its credit score.
[b] The probability of default comes from the migration analysis in table 4.
[c] Losses are expressed as a percent of the total debt in the portfolio.
[d] The unexpected losses will exceed UL(α) with a probability α.
[e] Value-at-Risk (VaR) is the sum of expected and unexpected losses. The VaR(1-α) represents the total capital needed to protect against both expected and unexpected losses at a (1- α) solvency rate.

Table 6. The KMV Model

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

Notes: [a] Each farm is assigned into a class based on its value of distance-to-default.
[b] Losses are expressed as a percent of the total debt in the portfolio.
[c] The unexpected losses will exceed UL(α) with a probability α.
[d] Value-at-Risk (VaR) is the sum of expected and unexpected losses. The VaR(1-α) represents the total capital needed to protect against both expected and unexpected losses at a (1- α) solvency rate.

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

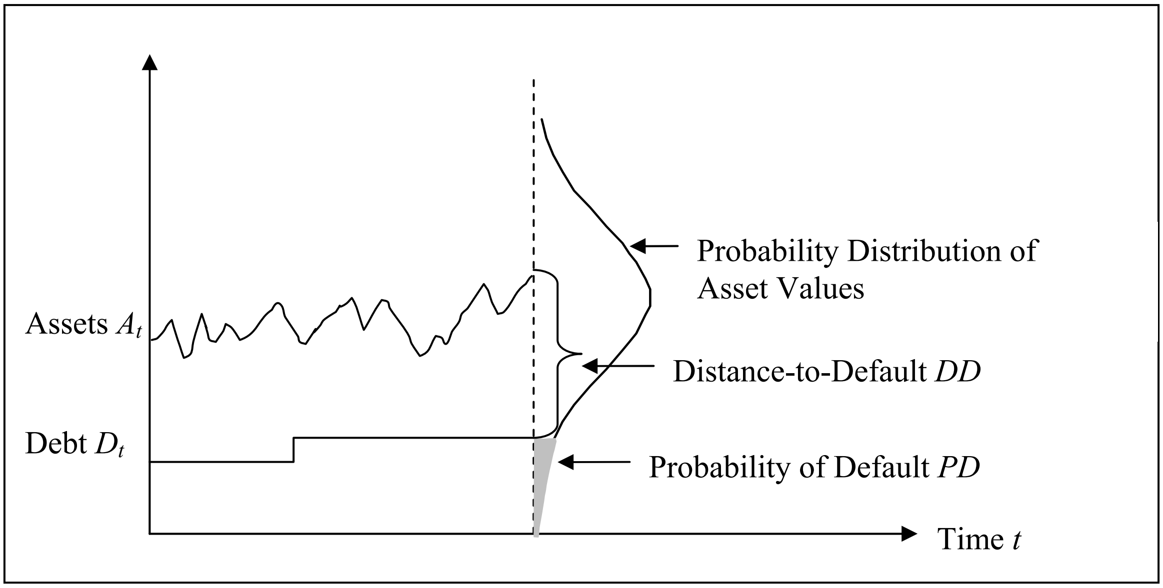
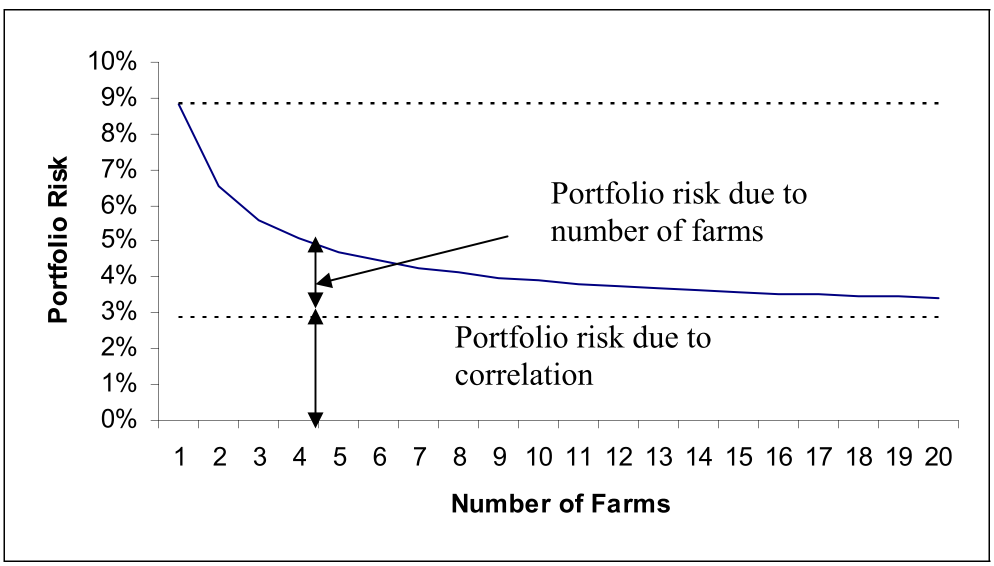


Figure 2. Effects of Number of Farms and Correlation on Portfolio Risk



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

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

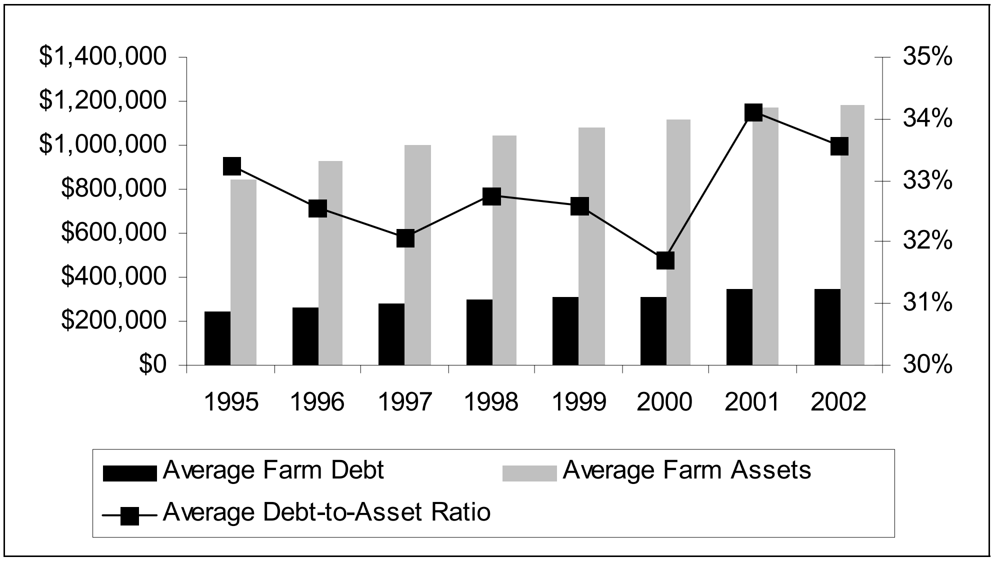


Figure 4. Default Rates

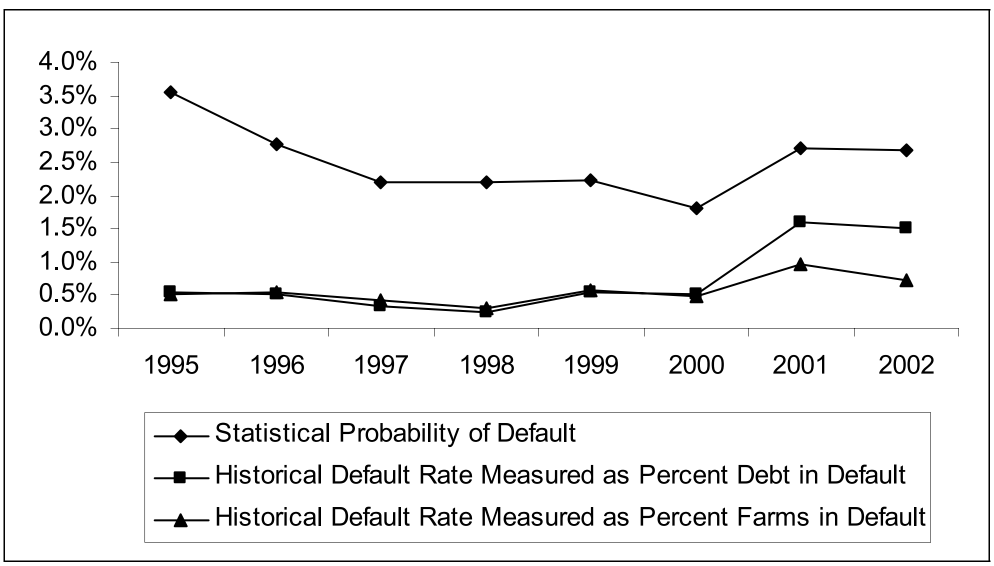


Figure 5. Loss Given Default for Farm Debt

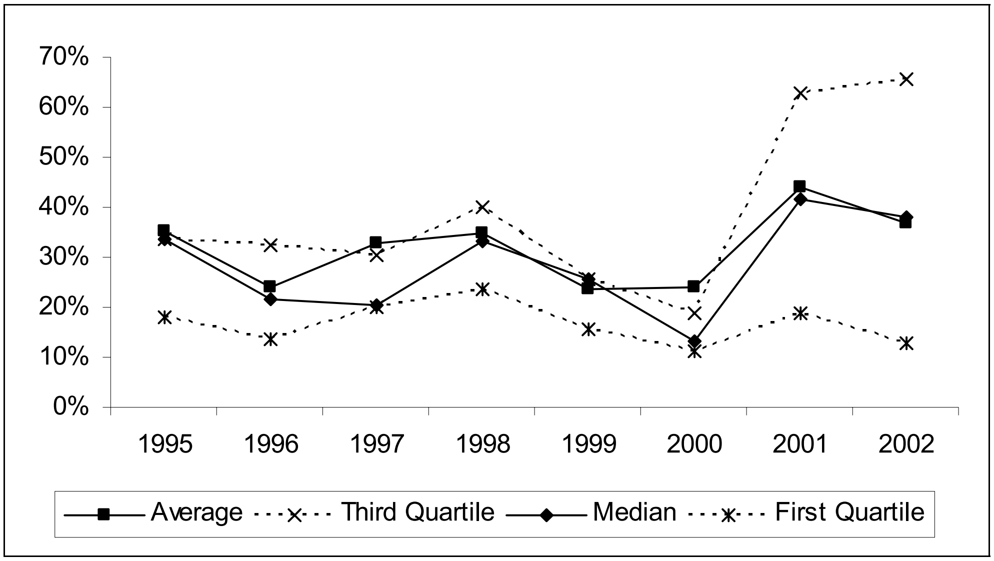
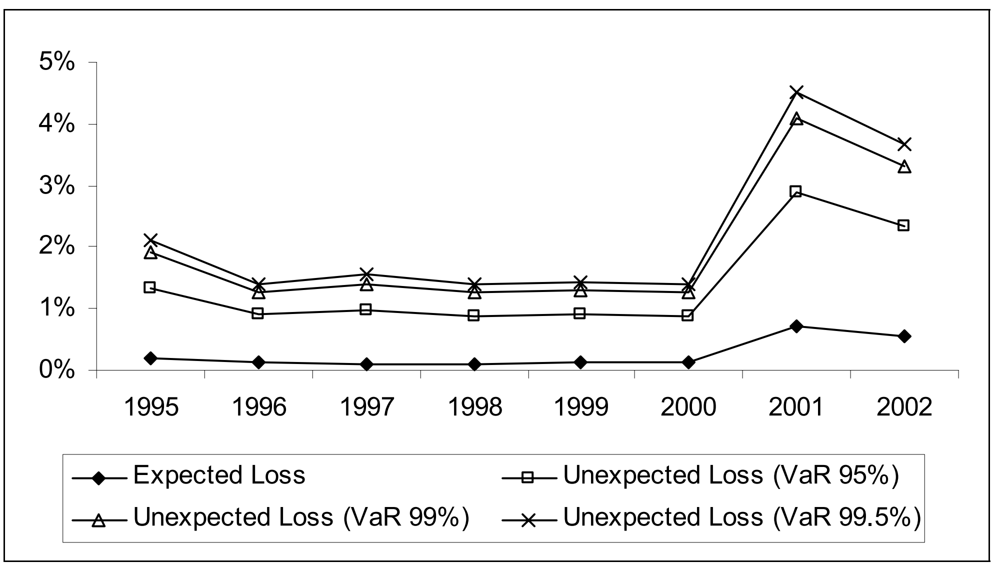


Figure 6. Expected and Unexpected Losses



Adapting Credit Risk Models to Agriculture

Lyubov Zech and Glenn Pederson*

Abstract

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

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

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Introduction

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

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

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

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

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

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

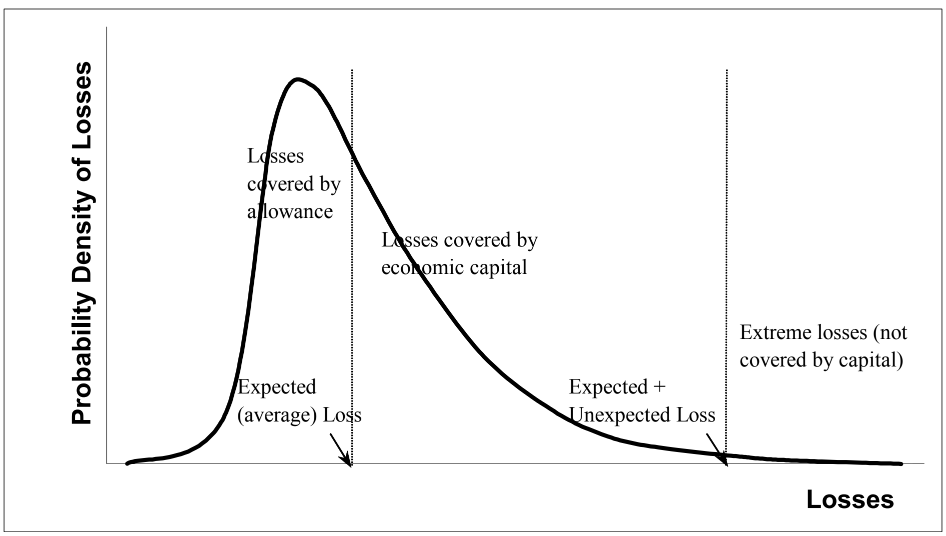
The second objective involves the application of the model to a representative Farm Credit System association, AgStar Financial Services, ACA. This objective includes appropriate parameterization of the model based on historical data consistently with the regulatory guidelines of the New Basel Capital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

Loan Loss Characteristics

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

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

Figure 1: Probability Density Function of Loan Losses



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

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

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

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

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

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

Basel Capital Accord

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

Model Selection

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

Table 1: Summary of Major Credit Risk Models

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

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

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

CreditRisk+ Overview

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

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

Figure 2: Model Structure

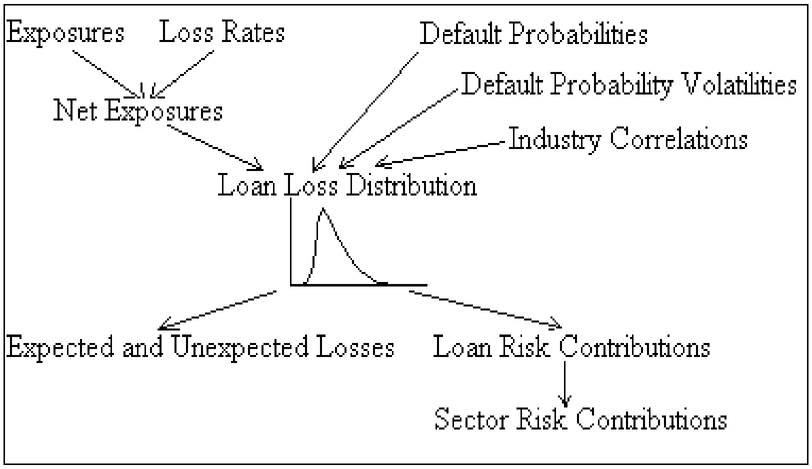


Figure 2 shows a brief overview of the model structure. The model inputs are exposures, default rates and their volatilities, and correlations of default between sectors (defined as industries in this study). The model inputs are exposures, default rates and their volatilities, and correlations of default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

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

Model Parameterization

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

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

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

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

Default Probabilities and Their Volatilities

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

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

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

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

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

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

Default Rate Volatility

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

Risk Migration

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

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

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

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

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

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

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

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

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

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

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

Loss Given Default

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

Table 5: Loss Given Default Rates

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

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

Sector Analysis

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

Table 6: Correlations of Default Between Industries in AgStar Data

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

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

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

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

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

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

Market and Operational Risks

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

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

Model Results

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

Table 8: Loan Loss Distribution Summary

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

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

Capital Adequacy

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

Table 9: Allowance for Loan Loss

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

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

Table 10: Economic Capital Under Various Confidence Levels

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

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

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

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

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

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

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

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

Stress-Testing

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

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

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

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

Table 14: Stress-Testing at 99.97th Percentile

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

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

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

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

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

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

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

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

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

Conclusions

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

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The Impact of Conservation Reserve Program Enrollment on Local Job Growth

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The Impact of Conservation Reserve Program Enrollment on Local Job Growth

The Conservation Reserve Program (CRP) was established by the Food Security Act of 1985 and began enrolling farmland in 1986. Under this voluntary program, the U.S. Department of Agriculture contracts with agricultural producers and landowners to retire roughly 34 million acres of highly erodible and environmentally sensitive cropland from production for a period of 10-15 years. Enrolled land is planted to grasses, trees, and other cover, thereby reducing erosion and water pollution, providing other environmental benefits, and reducing the supply of agricultural commodities. CRP rental payments give participants a stable source of revenue and CRP's impact on production increases the market price of commodities for all crop farmers. The program's benefits to the environment, CRP participants, and other crop farmers have made it a recurring focus of subsequent farm program legislation; but the program's potential impact on hired farm labor and off-farm jobs in nearby communities has been a concern.

As with other farmland retirement programs, enrollment in CRP could reduce demand for farm inputs and agricultural marketing services unless cultivation is expanded by an equivalent amount elsewhere. While CRP rental payments compensate participants for the losses they incur from idling their land, CRP does not reimburse others for associated reductions in demand. As a result, if cultivation on nonenrolled land does not increase as CRP land is taken out of production, demand for local labor could decline as participation in CRP increases. For this reason, enrollment in CRP is capped at 25 percent of each county's total cropland unless permission to waive the cap is requested by county officials and granted by USDA. On the other hand, CRP provides environmental benefits which can enhance natural resource based tourism and recreational spending. Our aim in this paper is to determine if high levels of CRP enrollment had a measurable impact on job growth in affected counties during the program's first 15 years of operation.

Analytical Approach

Most research on CRP's economic impacts has relied on input/output models, such as IMPLAN, to estimate what is likely to happen as farmland is taken out of production. Studies by Martin, et al. (1988), Standaert and Smith (1989), Mortensen, et al. (1990), Hines et al. (1991), Hyberg, et al. (1991), Siegel and Johnson (1991), Dodson, et al. (1994), and Otto and Smith (1996) generally find that CRP could have a small negative impact on areas with high CRP participation. While providing a rough estimate of the potential adjustments local communities might face as farmland is retired, such simulations do not necessarily reflect how local economies actually adjust.[2] Our approach examines job growth trends before and after CRP was

[2] Input/output models capture economywide linkages at one point in time, but they hold these relationships constant when estimating the effects of subsequent policy changes. As the size of the CRP changes, industrial sectors, workers, and factor owners are expected to change in predictable ways. But as farm commodity prices change, previously uncultivated land may be planted, reducing CRP's impact on demand for farm-related goods and services. And as the program's environmental benefits begin to accumulate, other business opportunities not anticipated by existing input/output relationships, such as recreation, can emerge, altering the impact of a policy shock on job growth.

enacted and compares trends in counties with high levels of CRP enrollment with similar counties having little or no CRP enrollment. To our knowledge, this is the first nationwide econometric analysis of how job growth in rural counties reacted as land was enrolled in the CRP during the late 1980s and early 1990s.

In measuring the local importance of CRP, the enabling legislation implicitly adopted the proportion of each county's total cropland enrolled in CRP, capping it at 25 percent. After 1990, the mean proportion of cropland enrolled in CRP among counties with acreage in the program was roughly 6.6 percent. This is a reasonable metric when the primary concern is CRP's effect on farms and farm-related industries. But if the primary concern is with broader measures of community well-being, such as the change in total employment, high CRP enrollment relative to cropland may have little effect on the local economy if farming is a minor source of economic activity. A more direct measure of the local economic importance of resources retired by the CRP is the proportion of total household income received by county residents from CRP rental payments.[3] The mean rental-payment-to-income ratio among participating counties was remarkably stable during the early 1990s at about 0.75 percent. The two measures of CRP's local importance are positively correlated, but they measure different aspects of the program's importance.

To focus on locales most likely to be affected by cropland retirement, only counties in which farm employment comprised more than 5 percent of jobs in 1980 are considered. Furthermore, only counties in the contiguous 48 States that had an urban population of less than 20,000 in 1980 are analyzed. The resulting universe is composed of 1,481 counties located throughout the country, but concentrated in the Plains. These counties accounted for 79 percent of land enrolled in the CRP in both 1990 and 2002.

We further identify counties in which CRP is relatively important, based on the ratio of average CRP rental payments during 1991-1993 to total household income in 1985 (adjusted for inflation).[4] Focusing on counties with a payments-to-income ratio exceeding 2.75 percent and having more than 5,000 acres enrolled in the program yields 195 high-CRP counties, most of which were in the Plains. These high-CRP counties were matched with similar counties having little or no CRP enrollment to highlight CRP's impact on job growth trends. Figure 1 shows the location of the 195 high-CRP counties and their low-CRP matches.

To assess CRP's impact on the job growth process, we develop a single-equation, reduced-form rural job growth model based on previous literature. Four groups of explanatory variables are used in the analysis in addition to measures of CRP's local importance: (1) pre-CRP measures of employment and population change, (2) pre-CRP industrial and farm structure

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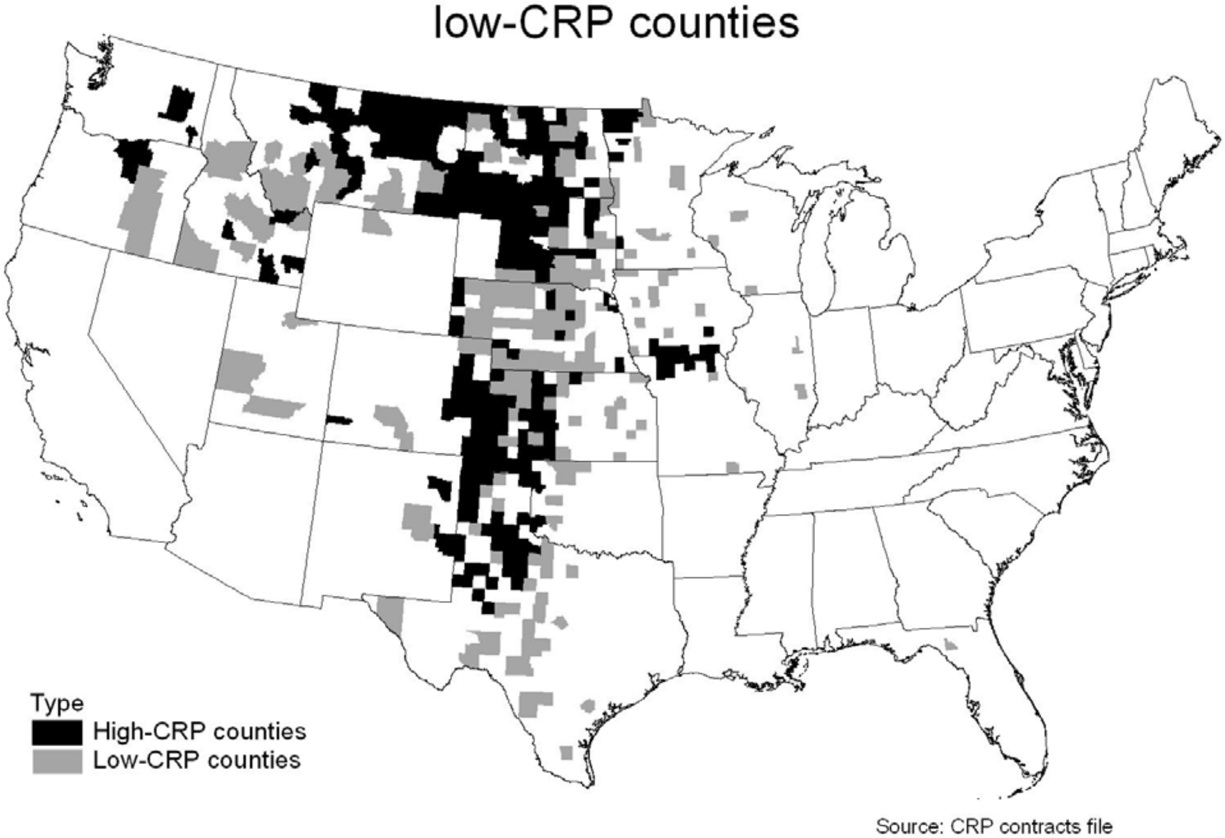
[3] Because we do not want the denominator of our measure to be influenced by CRP, we use pre-CRP estimates of county cropland and total household income to standardize CRP enrollment and rental payments, respectively.

[4] The program was nearly fully implemented by 1993. Using a 1991-93 average allows us to assess both the short-term impacts of CRP enrollment as well as impacts over a longer period, after local economies had time to adjust to the retirement of county farmland.

measures, (3) quality of life/amenity measures, and (4) pre-CRP demographic measures. To avoid biasing the estimated parameters, our non-CRP explanatory variables are from before CRP was enacted whenever possible. The dependent variable measures county employment change after 1985, as land began enrolling in the CRP. To capture both the short- and long-term response to CRP enrollment, employment change is measured over two periods—1985-1992 and 1985-2000. The specific measures included in our analysis are discussed in the appendix.

Figure 1: Matched pairs of high- and low-CRP counties

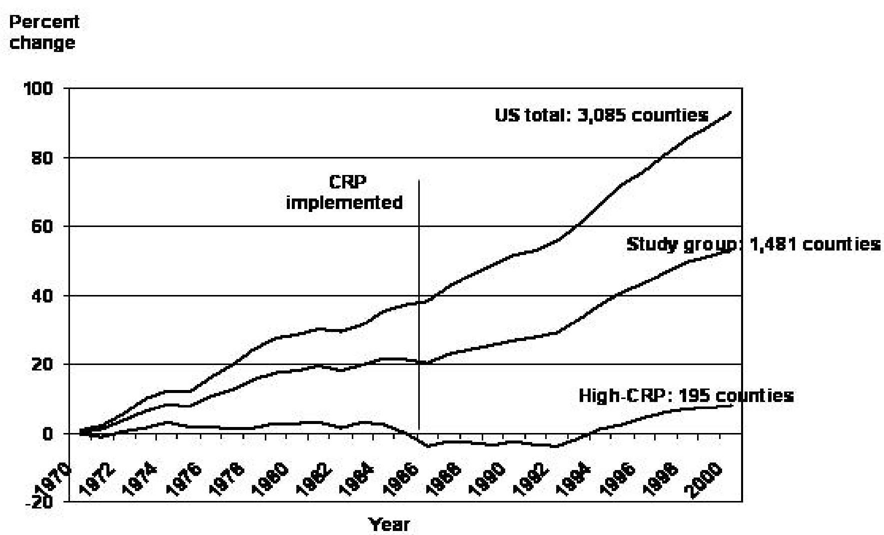


Our database includes over 45 measures that previous studies have associated with job change or that reflect local agricultural conditions. While these explanatory variables should capture the independent effects of many county characteristics potentially related to employment change, several socioeconomic measures are highly correlated, with no *a priori* reason for selecting one over the other. To avoid statistical problems from estimating relationships with an over-identified model, in addition to a standard analysis including all explanatory variables, a backward stepwise regression procedure narrows the set of variables.

Although the selection criteria provide a reasonably homogeneous group of observations, the resulting counties still exhibit enormous variation in socioeconomic factors. This variability, coupled with the complexity of the economic growth process, invites erroneous estimates due to misspecified models. One approach to testing for program impacts where the underlying process is complex is the use of quasi-experimental, or matched-pair, control group analysis (Bohm and Lind, 1993; Reed and Rogers, 2003). Intuitively, if high-CRP (treatment) counties were compared to otherwise identical low-CRP (control) counties, differences in economic performance between the two groups would demonstrate the effects of high CRP enrollment. In reality, the matches are imperfect so econometric analysis is still required, but the use of matched-pairs should help clarify relationships.[5]

In theory, the standard econometric approach should provide efficient, unbiased estimates of CRP's influence on job growth trends. However, in practice there are several reasons for preferring a more controlled analytical design. First, enrollment in the CRP likely depends on the economic health of the community. While all environmentally sensitive land is eligible for enrollment, the program initially appealed most to owners of farmland with below-average productivity that didn't have particularly high value for nonfarm uses. That is, CRP use was most heavily concentrated in isolated areas with relatively poorly performing economies—not in fast growing areas. This can be seen in figure 2.

Figure 2: Average job growth, 1969-2000



Source: ERS analysis of BEA Employment Files.

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[5] Ideally, counties should be similar in every respect except for the amount of CRP-eligible land, with low-CRP counties classified as such because their land was ineligible based on environmental sensitivity criteria. Unfortunately, it seems likely that some low-CRP counties are such because their eligible lands were too productive or too valuable for nonfarm uses to make enrollment in the CRP attractive. To the extent that considerations other than program eligibility led low-CRP counties to enroll fewer acres, our matched-pair comparisons will overstate the impact that CRP enrollment has on socioeconomic trends.

Counties with a high ratio of CRP rental-payments-to-income (greater than 2.75 percent) tended to have anemic local economies both before and after CRP was enacted in 1986. So the appropriate question is not whether high-CRP counties have performed worse than other counties, but whether CRP has affected their relative economic performance. This is much easier to evaluate within a quasi-experimental control group (QECG) analysis where high-CRP counties can be compared with counties having similar pre-CRP job growth trends, economic structures, etc.

Another reason why the traditional econometric approach might not be very fruitful is that CRP is not a sizeable program in the aggregate and for most counties with CRP enrollment. After an initial ramp-up period in the late 1980s, CRP rental payments have held steady at $1.4 to $1.7 billion per year. This isn't much when compared to other Federal farm program payments, let alone to all the other government programs and market fluctuations that influence job growth trends. By isolating counties with sizeable CRP enrollments, QECG analysis focuses on those counties most likely to be measurably affected by the program. Furthermore, the stability of CRP payment streams (guaranteed for the life of the 10-15 year contract) reinforces the analysis of high-CRP counties as "treatment" subjects from a program analysis perspective. Local CRP enrollment and rental receipts were fairly stable once the program was up and running.

Finally, QECG analysis makes it easier to assess program impacts when the precise functional form of the relationship between CRP enrollment and job growth is uncertain. It seems likely that the relationship between CRP and job growth is nonlinear, changes over time, and varies with economic conditions. By comparing "treatment" counties with "control" counties, QECG analysis can standardize many of the incidental characteristics which might influence the CRP-job growth relationship while putting variations in CRP's local importance in stark relief.

Therefore, in addition to estimating a traditional job growth model based on 1,481 study counties, we also estimate a series of models based on matched pairs of high- and low-CRP counties. Potential matches were restricted to study group counties which were not themselves high-CRP (based on either enrollment or rental payments) at any time during the program's history and which had CRP use measures that were less than 50 percent of the high-CRP county being matched.[6] Unique matches were selected which minimized the "Mahalanobis distances" between the high-CRP counties and all possible combinations of eligible low-CRP counties.[7] The Mahalanobis distance measures the similarity between observations based on a set of key characteristics—the smaller the distance, the more similar the matching is, based on the

[6] Paired t-tests indicate that the mean values of CRP's local importance (based on enrollments and rental payments) in high-CRP counties and their matches differ by more than two standard deviations, with a 99 percent level of confidence.

[7] The Mahalanobis distance metric takes the form $d^2(\mathbf{X}_T,\mathbf{X}_C)=(\mathbf{X}_T-\mathbf{X}_C)' \sum^{-1}(\mathbf{X}_T-\mathbf{X}_C)$, where **X** is the vector of selection variables, T is the treatment (i.e. high-CRP) county, C is a possible control county, d is the distance between the two vectors, and $\sum$ is the variance-covariance matrix of possible control counties (Isserman and Rephann, 1995).

characteristics being examined. Matches were based on pre-1984 measures of population growth, population density, commuting patterns, racial mix, mining employment, and the importance of Federal farm commodity program payments. In addition, contemporaneous measures of land in forest and the presence of natural amenities were included because historical data were not available. The aim is to find matched pairs of counties which were very similar before CRP enrollment began, and to then compare their development as land is enrolled.

The traditional growth model takes the form:

$$\log (J_{i,t} / J_{i,1985}) = f(CRP_i, \mathbf{X}_i)$$

where $J_{i,t}$ is the number of jobs in county i at time t greater than 1985, CRP_i is the local importance of CRP (i.e., the proportion of county cropland enrolled or the ratio of CRP rental-payments-to-income) in county i during 1991-1993, and $\mathbf{X}_i$ is a vector of county i's pre-1985 socioeconomic and amenity characteristics hypothesized to influence local job growth.

For the matched-pair analysis, the difference in job growth trends between high-CRP counties and their matches were estimated as a function of differences in explanatory variables between matched pairs of counties. That is:

$$(\log (J_{Tt}) - \log (J_{Ct}))_i = f((CRP_T - CRP_C)_i, (\mathbf{X}_T - \mathbf{X}_C)_i)$$

where J_{Tt} is the ratio of jobs in high-CRP county i at time t relative to jobs in 1985, J_{Ct} is the identical ratio for jobs in the low-CRP county uniquely matched with i, $(CRP_T - CRP_C)_i$ is the difference between CRP's local importance in high-CRP county i (the treatment county) and its matching low-CRP county (the control county), and $(\mathbf{X}_T - \mathbf{X}_C)_i$ is a vector of the differences between each explanatory variable in high-CRP county i and its match. This approach examined whether differences in development trends between high-CRP counties and their matches could be accounted for by differences in pre-CRP socioeconomic factors and CRP's local importance (Blundell and Dias).[8]

Finally, shifts in mining activity had a pronounced impact on several high-CRP counties and their matches. In addition to including mining employment in 1980 as an explanatory variable, we also created a separate set of matched pairs that excluded counties where mining comprised over 5 percent of 1980 employment. Doing so clarified the relationship between community development and CRP, since variations in mining added substantial statistical "noise" to the data.

Empirical Results

Between the matched-pair and study data sets, the two measures of CRP's local importance, whether mining counties are excluded or included, and whether all variables are

[8] When parameters are estimated without a measure of CRP's local importance, the constant term measures the marginal effect on job growth trends of being classified as a high-CRP county. When CRP's local importance is included as an explanatory variable, the constant term is constrained to equal zero.

included in the model or a backward stepwise procedure is used, we have 20 different estimates of the relationship between CRP use and employment trends for each time period examined. By first looking at all of these estimated relationships, we can better assess the consistency of the matched-pair estimations

The results, reported in Table 1, are fairly consistent. CRP was associated with slower job growth in the short run. All coefficients were negative, and in 7 cases the coefficient was statistically significant at the .10 level or better. However, this negative relationship did not persist over the longer period. Apparently, if negative effects existed, they were short-lived. Over the long run, the sign on the estimated CRP coefficient shifted from negative to positive in all but one equation; in three equations this estimate was statistically different from zero at the 0.10 level. This suggests that local economies were generally able to adapt to any loss in jobs associated with the CRP.

Table 1: Summary of initial analyses of CRP's relationship with employment trends

	Sign of CRP coefficients:			
	Positive		Negative	
	All	Significant	All	Significant
Change in the number of jobs:				
1985-1992 (short-term)	0	0	**20**	**7**
1985-2000 (long-term)	**19**	**3**	1	0

Note: The data refer to the sign and statistical significance of the CRP regression coefficient in 20 different versions of the growth model, allowing the functional form and the list of independent variables to vary. In each case, the dependent variable is the log of the ratio of jobs at the end of the period relative to 1985 (when matched pairs are analyzed, the dependent variable is the difference in the log of the jobs ratio in high- and low-CRP counties). Statistical significance is based on a 2-tailed t-test at the .10 level.

We have argued that CRP's effect on job growth trends should be easier to detect using the QECG approach, and among the 7 analyses that report a significant negative relationship between CRP's local importance and job trends, 5 rely on the matched pairs of counties. Focusing on the results of the backward stepwise regression analysis of the matched pairs, we find that job growth trends are particularly sensitive to CRP enrollment relative to county cropland.[9] Table 2 presents the key results of a series of regressions on differences between high-CRP counties and their matched pairs. The first group of results shows whether differences in the size of the CRP payments-to-income ratio had a significant impact on county trends. Here

[9] This result is not unique to the backward stepwise regression analysis. The ratio of CRP payments-to-income was significantly related to job trends over 1985-1992 in only 1 of the 8 regressions it appeared in (these include standard and backward stepwise regressions of all study counties and study counties other than those with more than 5 percent employed in mining as well as similar analyses of matched-pairs of high- and low-CRP counties). On the other hand, the ratio of CRP enrollment-to-cropland was significant in 6 of the 8 regressions it appeared in. The remaining 4 regression analyses summarized in table 1 were for matched-pairs where neither measure of CRP's local importance was present (allowing the constant term to capture the marginal impact of being classified as a hgh-CRP county).

the results differ depending upon whether mining counties are included in the analysis or not. With mining counties excluded, job growth between 1985 and 2000 was positively related to CRP use.[10] The second group of results shows whether differences in the proportion of cropland enrolled in the CRP are related to differences in county trends. It appears that the relative size of CRP enrollment has a consistent, statistically significant, negative effect on job growth between 1985 and 1992, but little effect over the longer period.

One explanation for the discrepancy between the statistical significance of the coefficients for our two measures of CRP's local importance is that CRP-related job losses are most likely to occur in agricultural service centers. Counties with the highest CRP payments-to-income ratios have very low populations, are heavily dependent on farming, and lack significant numbers of nonfarm businesses. However, counties with the highest proportions of *land* in CRP may still have small towns with nonfarm businesses that could be adversely affected by declining sales of farm inputs and services.

Table 2: CRP's association with employment trends, 1985-2000

	Matched pairs[1]		Matched pairs/no mining[1]	
	Beta	Adj. R^2	Beta	Adj. R^2
CRP payments/income ratio[2]				
1985-1992 employment change	-0.0020	0.33	-0.0007	0.43
1985-2000 employment change	0.0014	0.38	**0.0045***	0.37
CRP enrollment/county acreage ratio[2]				
1985-1992 employment change	**-0.0027***	0.34	**-0.0028****	0.45
1985-2000 employment change	0.0009	0.38	0.0001	0.36

Source: Economic Research Service calculations using data from the 1980 Census of Population, the 1982 Census of Agriculture, the Bureau of Economic Analysis, and the CRP Contracts file.

* and ** indicate the regression coefficient is statistically different from 0 at the .05 and .01 level of significance, respectively. Beta represents the standardized regression coefficient for the CRP variable. Adjusted R^2 indicates the portion of variation explained by the regression.

[1] There are a total of 195 high-CRP-low-CRP matched pairs; when counties with more than 5 percent employed in mining in 1980 are excluded, this number drops to 190.

[2] When the difference-in-difference equations include a continuous variable measuring CRP's local importance, the constant is constrained to equal 0.

To investigate this issue further, we focus on the matched pair data set as these counties all have relatively low population densities.[11] By including a population density-CRP interaction term in the regression, we can measure CRP's differential impact on local communities as

[10] Mining employment was very volatile during the study period with employment increasing rapidly in some areas and decreasing rapidly in others. As a result, neither a continuous variable measuring the proportion of local jobs in mining nor a dummy variable for mining counties was effective at capturing mining's impact.

[11] This analysis was replicated for all counties remote from major cities and lacking towns of 2,500 or more. Results were generally consistent with those reported in table 3.

county population density varies. Because agricultural service centers may have been losing out to larger centers during this period, we also include an interaction term (percentage employed in agriculture multiplied by population density) to reflect any tendency for employment loss to be greater in more densely settled agricultural areas over the study period. The results of these analyses indicate that the negative effects of CRP on the number of jobs in the county were stronger in more densely settled rural counties than in thinly settled counties (Table 3). This was true over both the short and the long run, but the CRP coefficient was slightly higher in the long run equation while the absolute size of the CRP-density interaction term was noticeably smaller. The net result was that the association between CRP and depressed job growth in more densely populated rural counties was not nearly as strong in the long run.

Table 3: Interaction between population density and CRP's impact on nonfarm job growth

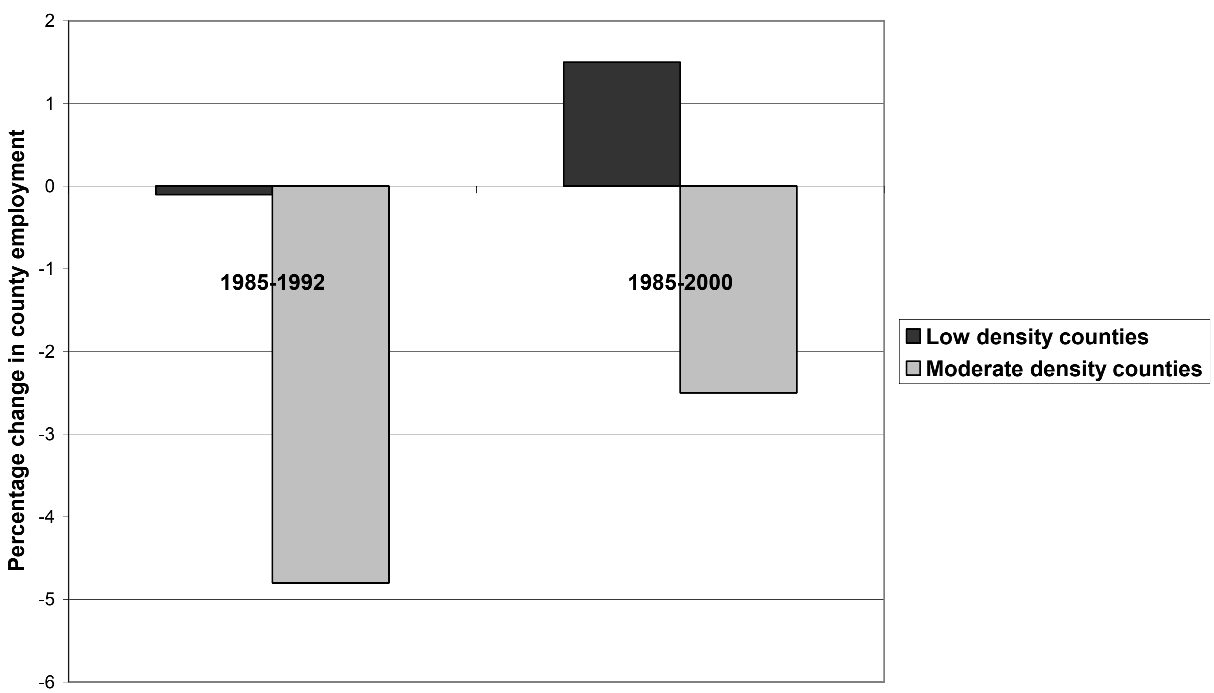
	Short term job growth (1985-1992)		Long term job growth (1985-2000)	
	Beta	t-statistic	Beta	t-statistic
CRP payments/income ratio	**0.232**	**2.26***	**0.247**	**2.28***
Population density, 1980 (log)	-0.286	2.05*	-0.012	0.08
Population density x CRP ratio	**-0.354**	**3.90****	**-0.201**	**2.20***
Agricultural jobs, 1980 (%)	-0.507	4.69**	-0.027	0.23
Population density x agricultural jobs	0.141	1.41	0.009	0.92
Population under 18, 1980 (%)	0.226	3.66**	0.243	3.70**
Black population, 1980 (%)	-1.142	2.25*	-0.238	3.68**
Mining jobs (%)	-0.302	4.71**	-0.133	2.02*
Working outside the county, 1980 (%)	--	--	0.122	1.66
Median household income, 1979 (log)	-0.177	2.79**	--	--
Great Plains dummy	-0.209	2.90**	-0.158	1.92
Land in forest (%)	--	--	0.256	3.38**
Govt. payments/total income, 1981-83	--	--	-0.268	2.40*
Wheat/total farm sales, 1982 (%)	-0.126	1.74	--	--
Adj. R^2	0.341		0.321	

Source: Economic Research Service calculations using data from the 1980 Census of Population, the 1982 Census of Agriculture, the Bureau of Economic Analysis, and the CRP Contracts file. All variables represent the difference between the level in each high-CRP and its matching low-CRP county, excluding pairs that include a county with more than 5 percent employed in mining. The first 5 variables are included by default while the remaining variables were selected by the backward stepwise procedure from among all explanatory variables based on the statistical significance of their contribution. The constant term was constrained to equal 0.

* and ** indicate the regression coefficient is statistically different from 0 at the .05 and .01 level of significance, respectively. Beta represents the standardized regression coefficient for the CRP variable. Adjusted R^2 indicates the portion of variation explained by the regression.

The marginal effect of CRP in thinly and more densely populated rural counties is easier to see in Figure 3. This figure shows the estimated impact of CRP on employment change as the difference in the ratio of CRP payments-to-income between low- and high-CRP counties increases from 0 to 4 percent. For low-density counties (those with fewer than 2 persons per square mile), CRP appears to have made little difference for employment change in either the short- or long-term. For higher density rural counties (those with more than 9 persons per square mile), the effect of a 4 percentage point increase in the ratio of CRP payments-to-income on county employment growth was substantial in the short-run, but effects dissipated over time as local economies adjusted. We interpret these results to mean that CRP had its most negative effects on jobs in counties with agricultural service centers, but that these effects were largely confined to the short term.

Figure 3: Nonfarm job growth in counties with low and moderate population density



Note: The bars indicate the estimated change in job growth if a county's ratio of CRP rental payments-to-household-income increased from 0 to 4 percent, holding other county characteristics constant. Low density counties have fewer than 2 persons per square mile. Moderate density counties have more than 9 persons per square mile. (The average for all 1,481 counties in the broader study group is 24 persons per square mile.)

These results are consistent with earlier estimates of CRP's likely effect on local economies in Oregon. In their forecasts, Martin, et al. (1988) projected that CRP would negatively affect farm dependent communities with small subregional agricultural supply centers. They expected farm dependent communities that were too small to support such centers (low density in our terminology) to be either unaffected or positively affected by CRP enrollments. Our results and the earlier forecasts by Martin, et al., focus on small isolated farming economies. Larger, more diversified economies are less likely to be significantly affected by CRP's impact on demand for farm-related goods and services.

Summary, Limitations, and Future Work

Previous attempts to estimate CRP's socioeconomic impacts have relied on: (1) deterministic models of the local economy, most often based on IMPLAN; (2) surveys of program participants and local government officials; and (3) econometric analyses of similar types of programs. While each of these approaches is useful and adds valuable insight into the adjustment process farming communities go through as they accommodate policy shocks, none can accurately evaluate what happens in response to changes in CRP enrollment. To our knowledge, this is the first systematic attempt to econometrically model the impact that CRP has had on farming communities nationwide based on observed data. These results suggest that local job growth may be sensitive to CRP enrollment, particularly in areas with small agricultural service centers. However, detrimental effects tend to be modest and fairly short lived. Rural economies, even those in undiversified farm-dependent areas, appear resilient enough to adapt to shifting demands and opportunities.

We designed our analysis to err on the side of finding a relationship between CRP and job growth. Nonetheless, limitations of the model and available data need to be acknowledged. Our analysis was conducted at the county level, so is not sensitive to changes in the distribution of jobs within counties. CRP could have much larger impacts on small geographic areas, such as individual towns, that are obscured by job growth elsewhere within the county.[12] Furthermore, while we have found evidence of a short-term relationship between CRP enrollment and job growth trends in some counties, we haven't demonstrated causality. CRP enrollment may be a more attractive option in areas experiencing economic problems whether or not that enrollment contributes to the area's problems. Finally, our matched pairs of high- and low-CRP counties were drawn from the same geographic area since high-CRP counties have unique characteristics that make them hard to match. To the extent that CRP's impacts are areawide, rather than confined to the county where CRP land is located, our analysis of differences between high- and low-CRP counties may be biased. The likely direction of the bias, if it exists, is unclear since CRP could have both positive and negative areawide impacts.

Our results hint at the complex economic changes that may have accompanied land retirement in counties with high levels of CRP participation. But to better understand how the adjustment process unfolded, we plan to perform cross-section time series analysis of changes in aggregate employment to see what the time lags were and what happened when CRP contracts began to expire after 1996. As time permits, we also plan to disaggregate the analysis to look at job growth in farm inputs and services industries as well as recreation and tourism industries to see how responsive they were to land retirement. Was the growth in recreation industries responsible for the longer term job growth patterns experienced by high-CRP counties or was the trend more widespread?

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[12] Research has shown that the relative size of program impacts is greatest within small geographic units (Hamilton and Levens, 1998) and that program impacts vary from community to community within a local area (Henderson, et al., 1992).

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Appendix: Modeling Rural Job Growth

We measure job growth as the natural log of the ratio of the number of jobs in each county in 1992 or 2000 relative to its 1985 job count. In modeling rural job growth, a county's historic pattern of population and employment change are often key predictors. County changes in population and employment are included for both the 1970s and the years immediately preceding the introduction of the CRP (1982-85). In the 1970s, agriculture, mining, and manufacturing were all relatively prosperous and contributed to the rural rebound of the period. In contrast, these industries suffered in the 1980s. The inclusion of 1982-85 changes captures some of this decline. As with the dependent variable, these explanatory variables take the log form. Table A-1 provides the mean values of the population and employment change variables, expressed as simple percentage changes, for the study group, high-CRP counties, and their matched pairs.

Table A-1: Mean values of population and employment trend variables

Variable description	Units	Study counties	High-CRP[1]	Matched counties
Dependent variables--				
Post-CRP employment change:				
1985-1992 (short run)	Pct.	5.6	-3.7	1.4**
1985-2000 (long run)	Pct.	23.9	7.6	13.4**
Explanatory variables--				
Pre-CRP population change:				
1970-1982	Pct.	11.3	-3.2	3.3**
1982-1985[2]	Pct	-0.3	-2.3	-1.3**
Pre-CRP employment change:				
1970-1982	Pct.	17.6	1.6	13.5**
1982-1985[2]	Pct.	2.6	-1.7	0.3**

Source: BEA Income files.
** indicates that the difference between high-CRP counties and their matched pairs is significantly greater than 0 at the 0.01 level.
[1] High-CRP counties have an average CRP rental-payment-to-income ratio for 1991-93 exceeding 2.75 percent. Of the 1,481 study counties, 195 were high-CRP by this definition.
[2] We include 1982-85 trends separately because rural county growth was slower in this period than during the preceding 12 years.

Measures of initial industry structure are ubiquitous in studies of job growth. The basic assumption is that local trends reflect national trends. Industry structure is measured by the proportion of employed residents working in agriculture, manufacturing, mining, business services (finance, insurance, real estate, and other professional services), and recreation (eating places, amusement, and recreation, other than hotels) in 1980, based on Census of Population data. Three types of somewhat unique rural industrial expansion that began in the late 1980s are casino resorts, prisons, and large meatpacking plants. These expansions were not affected by CRP, yet could have major impacts in counties where they are located. To take account of the sometimes dramatic changes accompanying these types of development, dummy variables were included to reflect whether a county had any of these industries in 2000.

Because CRP primarily affects farming-dependent areas, several agricultural variables in addition to employment were included in the analysis. Farm sales in 1982 relative to 1980 household income and farm income from government payments in 1981-83 relative to total personal income over this 3-year period were included to better measure the farm sector's importance to the local economy.[13] Also included were the percentage of county land in crops, the percentage of county farmland that was irrigated, the percentage of farm sales by type (livestock, all grains, and wheat), and to reflect farm size, the proportion of sales going to very small farms (under $20,000 sales) and large farms (over $250,000 sales). The proportion of farm operators working off-farm over 200 days a year was included, since the availability of off-farm work might enhance CRP participation. Finally, the ratio of CRP enrollment-to-total-cropland or the ratio of CRP rental payments to county household income is included to measure CRP's local importance. All of these data, with the exception of CRP and commodity program payments and county income were from the 1982 Census of Agriculture. Government payments and income for 1981-83 were from the BEA, and household income was from the 1980 Census of Population. CRP enrollment and rental payments were calculated from data reported in the CRP contracts file. Mean values of the industry and farm structure variables are presented in Table A-2.

The final set of economic measures reflects local labor market conditions. Higher employment rates and higher incomes might encourage local job growth through migration, but might discourage new employers. These are measured by the proportion of the population employed in 1980 and the log of median household income in 1979. The percentages of young adults (ages 25-44) who completed less than 12 or at least 16 years of school are also included. In general, both earnings and the likelihood of employment rise with education.

The attractiveness of an area is a function of its access to services and other amenities. Access to services is measured by whether the county was adjacency to a metropolitan area in 1983 (represented as a 0/1 dummy variable) and the log of its population density in 1980. The growth potential of a county may also depend on the percentage of its residents commuting outside the county to work. Finally, because the Great Plains has its own unique characteristics, a dummy variable indicates whether or not the county was in the Plains.

A series of demographic variables captures the effects of race, ethnicity, and age on the community growth process. The percentages of the population classified as Black, Hispanic, or American Indian were included in the equation, as was the percentage of the population under 18 years of age and over 62 years of age. All of the labor market and demographic variables were from the 1980 Census of Population.

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[13] Goetz and Debertin (1996) found that farm program payments were negatively associated with population change, controlling for a number of farm and industry measures. Van der Sluis and Peterson found a similar relationship, although they attributed it to cropland diversion requirements (1998).

Table A-2: Mean values of industrial and farm structure variables

Variable description	Units	Study counties	High-CRP[1]	Matched counties
Local economic characteristics:				
Agricultural employment, 1980	Pct.	16.7	31.7	24.7**
Manufacturing employment, 1980	Pct.	17.6	5.7	8.4**
Mining employment, 1980	Pct.	2.5	2.2	2.3
Business services employment, 1980	Pct.	4.2	3.9	4.2*
Recreation employment, 1980	Pct.	4.1	4.1	4.5*
Special development dummy variables[2]:				
Prison county dummy	0/1	2.6	1.0	0.0
Casino county dummy[3]	0/1	0.9	0.0	1.5
Meatpacking plant county dummy	0/1	1.4	0.5	1.0
Agricultural characteristics:				
Cropland/all land, 1982	Pct.	40.5	46.7	45.1
Irrigated farmland, 1982	Pct.	4.5	4.3	8.5**
Grain/total sales value, 1982	Pct.	29.5	38.4	31.5**
Wheat/total sales, 1982	Pct.	8.8	25.2	12.2**
Livestock/total sales, 1982	Pct.	56.2	51.5	61.6**
Govt. payments/total income, 1981-83	Pct.	1.6	6.0	2.6**
CRP enrollment-to-cropland, 1991-93	Pct.	8.0	21.3	5.1**
CRP payments-to-income ratio, 1991-93	Pct.	1.3	6.7	0.8**
Farm sales/household income, 1980	Pct.	0.8	1.9	1.4**
Farms w/ sales over $250,000 in 1982	Pct.	4.7	5.3	5.8
Farms w/ sales under $20,000 in 1982	Pct.	51.5	35.7	38.9*
Farmers working off-farm 200+ days	Pct.	28.0	17.9	21.0**

Source: 1980 Census of Population, 1982 Census of Agriculture, BEA Income file, and CRP Contracts file.
* and ** indicate that the difference between high-CRP counties and their matched pairs is significantly greater than 0 at the 0.05 and 0.01 level, respectively.

[1] High-CRP counties have an average CRP rental-payment-to-income ratio for 1991-93 exceeding 2.75 percent. Of the 1,481 study counties, 195 were high-CRP by this definition.

[2] The data reported for all 0/1 dummy variables represent the percentage of observations coded "1" rather than the mean for expositional ease.

[3] In Tunica, MS, a hitherto declining agricultural county, the development of a casino-hotel complex led to a sixfold increase in the number of jobs between 1990 and 2000. Because Tunica County was an extreme outlier, a dummy variable was included for that county in the study group equations. In addition, a dummy variable reflecting Somervel, TX, enters the equation for the entire sample to adjust for its inordinate growth due to the construction of a nuclear power plant in an adjacent county.

To measure scenic attractiveness, the presence of high mountains (0/1 dummy variable), the prominence of surface water (in logarithmic form) and forests (percentage of land area) are included in analyses of the entire study group. Also included are z-scores of several climate measures, including average January and July temperature, relative humidity in July, and sunny days in January, all of which were found to be associated with an area's attractiveness (McGranahan, 1999). For the matched-pair analysis, these amenity measures were replaced by the "natural amenity scale" developed by McGranahan (1999) to combine all of these factors into one measure. Table A-3 presents descriptive statistics for these variables.

Table A-3: Mean values of labor market, demographic, and amenity variables

Variable description	Units	Study counties	High-CRP[1]	Matched counties
Labor market and location characteristics:				
Civilian employment, aged 15-64, 1980	Pct.	62.7	64.9	65.6
Working outside the county, 1980	Pct.	19.0	10.9	12.9*
Under 12 years of school, aged 25-44	Pct.	23.4	17.2	16.5
College grads, aged 25-44, 1980	Pct.	14.1	16.9	17.4
Median household income, 1979	$	12,840	12,620	12,936
Population density, 1980	P/sq mi	24	5	10**
Adjacent to a metropolitan area, 1983	0/1[2]	41.3	15.9	22.6
Great Plains dummy variable	0/1[2]	27.1	80.0	59.5**
Demographic characteristics:				
Black population, 1980	Pct.	7.1	0.6	0.4
Hispanic population, 1980	Pct.	4.2	4.4	6.9
Native American population, 1980	Pct.	1.5	3.3	1.9
Population under 18, 1980	Pct.	29.7	29.8	29.3
Population over 62, 1980	Pct.	18.2	19.3	19.7
Natural amenity characteristics:				
High mountains dummy variable	0/1[2]	7.4	5.6	10.8
Water/total area (x 10)	Log	-2.1.	-6.5	-6.2
Land in forest	Pct.	26.7	3.7	8.5**
January days with sun (x 10)	Z-score	1.8	5.2	5.4
January temperature (x 10)	Z-score	-1.9	-8.3	-6.1*
July humidity (x 10)	Z-score	2.3	9.7	7.1**
July temperature (x 10)	Z-score	-2.6	-4.8	-5.0
Natural amenities scale (x 10)	Z-score	-3.6	-7.2	-6.6

Source: 1980 Census of Population and McGranahan (1999).
* and ** indicate that the difference between high-CRP counties and their matched pairs is significantly greater than 0 at the 0.05 and 0.01 level, respectively.
[1] High-CRP counties have an average CRP rental-payment-to-income ratio for 1991-93 exceeding 2.75 percent. Of the 1,481 study counties, 195 were high-CRP by this definition.
[2] The data reported for all 0/1 dummy variables represent the percentage of observations coded "1" rather than the mean for expositional ease.

Rural Small Business Finance -
Evidence from the 1998 Survey of Small Business Finances

Cole R. Gustafson*

Abstract

The 1998 Survey of Small Business Finances provides robust information on the financing of small businesses including an overview of their firm's organization, financial characteristics, and credit use. Information from the survey is used in this study to compare the financial characteristics of metro and rural small businesses. While many financial characteristics are similar, rural small businesses do own more land and depreciable assets, and have lower inventory and other current assets when compared with urban firms. Rural firms have relatively similar access to technology and financial services, although utilization varies. Both metro and rural small businesses rely on a wide variety of sources for financing, although rural small businesses have significantly more mortgages, loans from shareholders, and other types of loans, but fewer credit cards. Nonparametric rank order statistical methods were required because normality assumptions were violated due to asymmetric distribution of small firms.

Keywords: business, finances, rural, small, survey

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Rural Small Business Finance -
Evidence from the 1998 Survey of Small Business Finances

During revision of North Central Regional Research Project NC221, committee members identified rural business finance as one of four high priority areas of future research. In the past, agricultural economists have emphasized agricultural finance from farm, agribusiness, and financial institution perspectives (Barry and Robison). Economists have explored many aspects of small business finance, in general (Petersen and Rajan). Western Regional Research Project W167 was organized to explore rural finance issues from the development perspective. However, those studies did not provide in-depth analyses of rural small business financial management as their specific focus was on development finance and the appropriate role of public support programs. Moreover, the project was not renewed. Drabenstott and Meeker state, "Rural capital markets have not been widely studied, but many analysts believe that rural borrowers face less competitive markets, with fewer capital suppliers, and fewer financial products and services." Thus, a gap in rural small business finance research appears to exist at the present.

The purpose of this article is two-fold. A primary goal is to introduce newly available data from the 1998 Survey of Small Business Finances. This periodic Federal Reserve Bank survey provides robust information on the financing of small businesses including an overview of the firms' organization, financial characteristics, and credit use. The survey is the most comprehensive source of such information; no other source provides the breadth and detail of information for a nationally representative sample of small businesses (Bitler, Robb, and Wolken). An appealing feature of this survey is the delineation of rural and metro respondents. [1]Research on rural small business finance has been difficult in the past due to data limitations. Hopefully, ready access to rural small business financial data will stimulate additional investigation on the performance of rural capital markets and small business finance.

A second goal of this study is to present an overview of rural small business finance and delineate comparisons with metro small business firms. Counter to conventional wisdom, anecdotal evidence and the results of several case studies, rural small businesses are found to face equally competitive financial markets, have ready access to modern financial products and services, and possess similar capital structures relative to their metro counterparts.

Following sections of this article describe the 1998 Survey of Small Business Finances including the survey's history, content, sampling procedure utilized, and procedures for access. An overview of rural small business finance is then presented with comparisons made to metro

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[1]Documentation of the Survey refers to the distinction as urban and rural. However, the actual screening is on Census Metropolitan Statistical Areas (MSAs) which are defined as an area with more than 50,000 inhabitants. The term urban is generally reserved for places exceeding 2,500. Thus, the term metro is more exact and used in this article. Less inhabited areas will be referred to as rural as a synonym of non-metro since it is widely recognized within the profession. I am grateful to an anonymous reviewer who provided this clarification.

small business peers. Finally, an overview of rural small business finance and selected comparisons with metro small business peers are derived from the 1998 Survey of Small Business Finances.

The Survey of Small Business Finances

The Survey of Small Business Finances (SSBF) is conducted by the Federal Reserve Bank and collects demographic and financial information from 3,561 for-profit, nonfinancial, nonfarm small businesses (less than 500 employees) who were in business in the United States at the end of 1998. Similar surveys have been conducted in 1987 and 1993. Working papers, methodological documentation, codebooks, and full public datasets (SAS or PDF) are available online:

http://www.federalreserve.gov/pubs/oss/oss3/nssbftoc.htm

Information collected in the survey includes:

- Demographic information on the owners and characteristics of the firm including SIC, MSA, and Dun & Bradstreet industry classifications;
- Inventory of firm's deposit and savings accounts, leases, credit lines, mortgages, loans and other financial services. For each financial service, the supplier is identified;
- Characteristics of financial service suppliers including type (e.g., bank, individual), method of conducting business, patronage, and reasons for choosing source;
- Experience in applying for credit in the past 3 years;
- Experience with trade credit and equity injections;
- Firm's income and balance sheet; and
- Credit history, credit scores for both firm and owners, and Herfindahl index of concentration.

The sample for the survey was drawn from the Dun & Bradstreet Market Identifier file which represents approximately 93 percent of full-time business activity. Sampling was done according to a two-stage stratified random sample. In the second stage, small businesses with more than 20 employees and minority-owned firms were oversampled to ensure their numbers would be sufficient for statistical testing. An overall response rate of 33 percent was obtained. Appropriate sample weights are included in the public dataset.

Bitler, Robb, and Wolken summarize key survey findings. Over 83 percent of the small businesses had less than 10 employees and over one-half were organized as sole-proprietorships. The primary activity for 43 percent of the firms was business or professional services. Commercial banks were the primary supplier of financial services and 55 percent reported having loans, capital leases, or lines of credit at year end. Trade credit was used by 60 percent of small businesses in 1998, but interest rates were quite high; 2 percent a month was not uncommon. Three-fourths of the firms used computers, primarily to access the internet, inventory management, and bookkeeping.

Data from this survey have been used to explore lending practices of rural banks involved in mergers (Walraven) and portfolio decisions of small agribusinesses (Holmes and Park). Walraven presents a table of summary statistics that compares demographic and financial characteristics of rural and metro small businesses. He concludes that rural small businesses are older, have greater sales and assets, experienced fewer business and personal bankruptcies, and have been denied trade credit less frequently.

Rural Small Business Finance

Historically, the financial performance of credit markets and small businesses in rural areas has been a topic of active professional discourse. At the center of the debate is whether or not gaps exist in rural financial markets. Edelman notes that: 1) rapid concentration of bank assets due to merger activity may limit lending to rural businesses, 2) financial market regulations impose greater costs to smaller lenders that are characteristic of rural communities, 3) rural borrowers with unique credit needs (large amount, start-up, unfamiliar venture) face greater difficulty obtaining credit, 4) rural equity markets are unorganized and virtually nonexistent, 5) rural infrastructure is difficult to finance, and 6) financing of housing construction and ownership is more difficult in rural areas. Barkema and Drabenstott expand on the difficulties rural areas have maintaining fundamental physical and social infrastructure including roads, utilities, and educational and health services. They proceed to highlight the impending need to invest in digital communication infrastructure. Markley and McGee conducted several detailed case studies in Arkansas, Massachusetts, Michigan, and North Carolina and found that credit gaps exist in all regions of the country, but are especially acute in rural areas. They proceed to offer several recommendations for improving the effectiveness of development finance programs that utilize public funds.

Other studies have not found significant shortfalls in rural small business financial markets. Surveys of small businesses in Arkansas and Illinois found adequate availability of debt and equity capital (Gruidl, Lamberson and Johnson). Shaffer and Pulver (1985) compared capital market performance in thinly and densely populated areas of Wisconsin and concluded they functioned relatively well for small businesses in both locations. In a later study, Shaffer and Pulver (1990) found that availability of capital is not a widespread problem and no one type or stage of business had difficulty acquiring capital.

Two comprehensive assessments of rural small business finance was undertaken in 1997. First, USDA published its assessment, *Credit in Rural America*. The report concluded that rural financial markets work reasonably well but those with low incomes, low skills, and lack of collateral have particular problems with access to credit and financial services. The report goes on to state that any public financial market failures are neither endemic to nor epidemic in rural America. Therefore, policies which provide untargeted subsidies to a broad range of rural lenders or borrowers are unlikely to be cost effective. A conference organized by the Federal Reserve Bank of Kansas City came to a similar conclusion (Drabenstott and Meeker). Conference participants reviewed the importance of capital to the rural economy, discussed shortcomings in those markets, and identified opportunities to improve access to capital for rural borrowers. A consensus was that rural businesses have a smaller menu of products and often pay more for access to capital. This is due in part to the limited and declining supply of loanable funds, bank consolidation, and undeveloped equity markets in rural areas. Expanded secondary markets were identified as a source of increased liquidity, but development has been slow. Technology and globalization will likely diminish the geographical impediments in rural financial markets.

Also in 1997, the Rural Policy Research Institute (RUPRI) convened a rural finance taskforce. The taskforce found most rural borrowers with relatively routine credit needs are well served by existing lenders. However, borrowers with large debt capital needs, borrowers needing debt capital for start-up businesses, and borrowers needing debt capital for businesses unfamiliar to their lenders can expect difficulties in obtaining the credit they request.

Past studies evaluating the performance of rural financial markets have not provided definitive assessments primarily because they relied on selected localized information, case studies, and anecdotal observations. Comprehensive financial survey information may alleviate these past shortcomings and provide the necessary quantitative data for statistical testing and extrapolation.

Financial Characteristics of Rural Small Businesses

In general, both metro and rural small businesses in the sample were strong financially (Table 1). On average, they were profitable, liquid, and solvent. Accounts receivable and inventory comprise nearly a third of total assets. Roughly 10 percent of assets are held in the form of cash. Land is a minor asset for most small businesses, whereas the average small business has a large investment in equipment. Trade financing in the form of accounts payable represents nearly a fourth of small business total financing.

An appealing feature of the SSBF for purposes of this study is the ability to distinguish between metro and rural small businesses who participated in the survey. Screening firms using the MSA/non-MSA variable yielded 2,782 metro and 779 rural firms, respectively. This sort formed the basis for the following comparative analyses in this article.

Traditional parametric statistical analyses that compare the financial characteristics of metro and rural small businesses proved futile because the data violated assumptions of normality. A common feature of small business financial data is the presence of many small firms. The majority of firms contained in the dataset are of relatively small size (as measured by either sales, total assets, or number of employees). However, larger firms are also present, but fewer in number, thus creating a long right tail when modeling the distribution function. Classifying the largest firms as outliers failed to restore normality. Further, no clear demarcation for selecting outliers was evident.

Initial t-tests of mean financial characteristics found few significant differences between metro and rural firms, despite high statistical power as evidenced by a large number of observations and a sizable difference in mean values. Using Shapiro-Wilk and Kolmogorov-Smirnov tests, normality of the probability distribution function was readily rejected (SAS Institute Inc.). Efforts to transform the data into a normal distribution were unsuccessful. Therefore, the nonparametric Wilcoxon rank order method was used for statistical testing. Essentially, the Wilcoxon method determines whether two samples of financial data (metro vs. rural) have arisen from the same probability distribution function. Among linear rank statistics, Wilcoxon scores are locally most powerful for identifying location shifts of the distribution (SAS Institute Inc.). Standard deviations are reported in the following tables, but readers are advised against using traditional t-test's for significance tests due to non-normality of data.

Even with the more general Wilcoxon statistical test, rural and metro small business firms were found to have few differences in financial characteristics. As shown in Table 1, rural small businesses were found to have statistically lower levels of inventory and other current assets and higher levels of land and depreciable assets. All other financial characteristics, including sales, costs of doing business, corporate taxes paid, and liabilities were not statistically different between metro and rural small businesses.

With respect to financial organization, the majority of firms are organized as sole proprietorships. Surprisingly, less than 6 percent of small businesses were organized as partnerships. Rural firms are significantly more likely to be organized as sole proprietorships as opposed to corporations. Rural firms may have access to fewer sources of equity capital.

Financial Accounts

Metro and rural small businesses both rely on a wide variety of sources for financing (Table 2). Surprisingly, rural firms utilize each source just as frequently and to the same degree as their metro counterparts.

Just about all metro and rural firms have a checking account with an average balance of $30,000. Savings accounts are far less frequent with only 22 percent of firms using one. Nearly half of metro and rural firms use an owner's or business credit card for transaction financing, although statistically, rural firms use both credit cards less frequently.

Firms in poor financial condition and those with limited access to capital often have multiple (split) credit lines to bridge their financial needs. The vast majority of metro and rural firms (over 80 percent) in this survey patronize one creditor. The average credit limit ranges from $144,470 for rural firms to $377,316 for metro firms, but the difference is not statistically significant. The actual amount borrowed on both lines is approximately one-half. The majority of these lines do require a guaranty, but not collateral.

Rural small businesses do rely more on mortgage financing as a source of capital than metro small businesses. The average balance of mortgages supporting rural small businesses is $160,686. Rural and metro small businesses utilize vehicle loans as a source of capital to the same extent (20 percent of firms). The average vehicle loan balance exceeds $25,000.

Neither metro nor rural small businesses utilize equipment financing extensively. Small business equipment is often so specialized with minimal salvage value that financing is difficult to obtain. Moreover, many small business equipment manufacturers may not have the financial capacity to offer financing programs.

Over one-fourth of rural and metro small businesses received loans from stockholders. Average loan size ranged from $108,523 for metro firms to $150,313 for rural firms. Rural firms do statistically utilize other types of loans to a greater extent than metro firms do. This may be related to rural firm's relatively greater investment in land and depreciable assets. Moreover, the majority of rural firms are organized as sole proprietorships, and transactions costs associated with personal forms of credit (e.g. home equity loans, loans from relatives, etc.) maybe lower for sole proprietors.

In addition though, credit options in rural areas may be more limited. Thus, rural firms would be expected to rely more heavily on mortgages, other loans, and larger stockholder loans than shorter-term financing such as credit cards, that metro small businesses do. When financial services are limited, small business owners often draw on personal forms of credit to finance either investment or operations. Thus, reliance on mortgage, shareholder and other loan types by rural small businesses could be construed as an indicator of inefficient financial markets in rural areas. If rural financial markets were as efficient as metro markets, rural small businesses would be provided with and optimally use a full range of financial products.

Financial markets are presumed to be most efficient when a large number of financial institutions compete against each other. A common measure of financial market competition is the Herfindal index which is created by taking the percentage market shares of each firm in the market, squaring them, and summing.. In this survey, rural small businesses operated in regions of statistically lower bank concentration as compared with metro small businesses. With less competition, banks have less incentive to supply a breadth of financial products to risky small businesses. However, this lower concentration does not apparently lead to lower frequency or amounts of credit as rural firms appear to utilize loan products equal to or even to a greater degree than metro firms. As described in the next section, access to financial services is also on par with metro small businesses.

Use of Technology and Financial Services

The majority of small businesses do use computers frequently for business purposes (Table 3). Most popular uses of a computer are for accounting/bookkeeping, email, and general administration. However, use of computers for financial services such as PC banking and online credit applications is limited.

Computer usage among rural small businesses significantly lags behind metro firms. Rural firms are less likely to use computers for banking, email, internet sales, and administrative functions. Interestingly, rural firms utilize computers for inventory management more frequently than metro firms. Greater distance may preclude vendors from performing that function for them.

Rural and metro firms are frequent users of trade credit and periodic users of transactions services. However, few small businesses use other financial services for cash management, credit, trusts, or brokerage. Rural firms use a statistically higher rate of credit services and lower rate of trust services, although both are infrequent.

With respect to trade credit, metro and rural small businesses purchase over two-thirds of their supplies on trade credit. Consequently, it is not surprising that they report an average number of twenty trade credit suppliers. Rural firms are offered more frequent cash discounts (28 percent). Almost a third of both metro and rural small businesses report repayment of trade credit after the due date. The average length of discount is 14 days and the average discount is 2.41 percent for rural firms and 1.46 percent for metro firms, although the difference is not statistically significant.

Creditworthiness

As measured by the Dun & Bradstreet credit score, rural small businesses possess statistically higher creditworthiness (Table 4). Metro and rural firms appear to have similar frequency of being denied trade credit and bankruptcy. Moreover, rural small businesses are statistically less likely to be delinquent on business obligations, but more reluctant to apply for mortgage loans for fear of being denied. Over 25 percent of rural small businesses reported being delinquent on business obligations.

Conclusions

The 1998 Survey of Small Business Finances provides robust information on the financing of small businesses including an overview of their firm's organization, financial characteristics, and credit use. Information from the survey is used in this study to compare the financial characteristics of metro and rural small businesses. Nonparametric rank order statistical methods were required when comparing dollar values of metro and rural small businesses because normality assumptions were violated due to the high concentration of small firms.

On average, rural and metro small businesses were strong financially and profitable. Accounts receivable and inventory comprise nearly a third of total assets. Rural small businesses tended to have lower inventory and other current assets but higher levels of depreciable assets and land. Most small businesses utilized computers, primarily for accounting/bookkeeping, administration, and email. Primary financial services are used for transactions and trade credit. Two-thirds of purchases involve trade credit from more than twenty trade credit suppliers, on average.

Both metro and rural small businesses rely on a wide variety of sources for financing, although rural small businesses have significantly more mortgages and other types of loans, but fewer credit cards. Whereas most metro small businesses were organized as either sole proprietorships or corporations, significantly more rural firms were organized as sole proprietorships. This, and their larger investment in fixed assets, may partially explain rural small business's greater reliance on mortgage, stockholder, and other types of loans for financial capital. Lack of bank concentration in rural areas does not appear to stymie rural small business access to either loans or financial services. Rural small businesses possess higher creditworthiness, but nearly one-fourth still report being delinquent on business obligations.

Preliminary results of the survey leave a number of unanswered researchable questions. First, it is unknown whether the lack of statistical difference between metro and rural firms is in fact due to few differences between the two groups or whether high variation and non-normal distributions of firm size within each group limits statistical power. Second, the results reflect only one observation in time, a period of relatively strong economic prosperity. Additional study utilizing either past or future survey results could provide more robust conclusions. Finally, a number of interesting financial differences characterizing rural small businesses (emphasis on longer term assets, more personal forms of finance, greater numbers organized as sole proprietorships, and higher use of computers for inventory management and administration) could be delineated with multivariate analysis and resolve unexplained relationships raised in this preliminary review of the dataset.

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Table 1. Financial Characteristics

Item	Metro (Weighted Mean)	Metro (Std.Dev.)	Rural (Weighted Mean)	Rural (Std.Dev.)
Income:				
Total sales	$1,064,665	2.74 E8	$664,088	8.71E7
Other income	14,764	5.88 E6	10,967	7.72E6
Cost of doing business	944,250	2.56E8	561,093	
Corp. tax	18,494	5.54E6	23,730	8.00E7
				5.46E6
Assets:				
Cash on hand	44,212	1.16E7	30,497	1.12E7
A/R	104,155	2.54E7	49,470	8.93E6
Inventory	79,803	3.06E7	69,438**	2.06E7
Other current assets	32,734	1.40E7	21,076*	9.66E6
Investments	14,441	6.03E6	19,529	2.13E7
Land, book value	30,799	1.31E7	39,947*	1.15E7
Depreciable assets	115,259	3.05E7	122,520*	3.17E7
Total assets	426,710	8.05E7	356,711	6.44E7
Liabilities:				
Accounts payable	66,306	1.40E7	43,465	1.60E7
Current liabilities	38,431	1.29E7	20,710	7.50E7
Total liabilities	261,456	5.90E7	194,199	4.50E7
	-------------percent-------------			
Organization:				
Sole proprietor	47	N/A	58**	N/A
Partnership	5	N/A	5	N/A
Corporation	45	N/A	33**	N/A

*Statistically significant based on Wilcoxon nonparametric linear rank test @ p < .05
**Statistically significant based on Wilcoxon nonparametric linear rank rest @ p< .01

Table 2. Source of Financing

Item	Metro		Rural	
	(Weighted Mean)	(Std. Dev.)	(Weighted Mean)	(Std. Dev.)
Have checking account (1 = yes, 2 = no)	1.05	9.01	1.07	9.51
If yes, average balance	$31,400	6.98E6	$29,096	7.77E6
Have savings account (1 = yes, 2 = no)	1.77	16.23	1.78	15.27
If yes, average balance	$63,230	1.03E7	$35,819	3.32E6
Use owner's credit card for business (1 = yes, 2 = no)	1.53	19.46	1.57*	18.28
If yes, average balance	$1,649	4.43E5	$1,011	3.11E5
Use business credit card (1 = yes, 2 = no)	1.65	18.59	1.69*	17.03
If yes, average balance	$2,558	3.43E5	$1,255*	1.09E5
Number of credit lines	1.19	17.94	1.10	17.33
If yes, credit limit	$377,316	8.03E7	$140,470	1.73E7
amount owed	$144,224	2.94E7	68,834	1.16E7
collateral required (1 = yes, 2 = no)	1.57	17.03	1.54	15.78
guaranty required (1 = yes, 2 = no)	1.39	16.81	1.44	15.74
Any mortgages? (1 = yes, 2 = no)	1.89	12.21	1.78**	15.25
If yes, principal owed	$279,887	2.56E7	160,686	2.34E7
Motor vehicle loan? (1 = yes, 2 = no)	1.80	15.70	1.79	15.07
If yes, principal owed	$25,254	6.10E6	29,310	2.40E6
Equipment loan? (1 = yes, 2 = no)	1.91	11.31	1.88	12.19
If yes, principal owed	$81,480	1.20E7	$90,253	2.37E7
Any loans from stockholders? (1 = yes, 2 = no)	1.72	15.94	1.74	16.31
If yes, principal owed	$108,573	1.32E7	$150,313	2.57E7
Any other loans? (1 = yes, 2 = no)	1.91	11.46	1.86*	11.09
If yes, principal owed	$118,499	1.94E7	$82,275	1.12E7
Herfindahl index 1 = 0 < herfindahl < 1000 2 = 1000 < = herfindahl < 1800 3 = 1800 < herfindahl		23.38	2.38**	13.47

*Statistically significant based on Wilcoxon nonparametric linear rank test @ p< .05
**Statistically significant based on Wilcoxon nonparametric linear rank test @ p< .01

Table 3. Use of Technology and Financial Services

Item	Metro		Rural	
	Weighted Mean)	(Std. Dev.)	(Weighted Mean)	(Std. Dev.)
Computer use (1 = yes, 2 = no)				
Used computer for business	1.21	15.86	1.35**	17.67
If yes, computer used for:				
PC banking	1.84	13.39	1.89*	14.00
Email	1.24	16.34	1.28	15.57
Internet sales	1.63	18.46	1.68	16.10
Credit applications on line	1.94	8.55	1.95	7.66
Inventory management	1.60	18.71	1.54**	17.20
Administration	1.17	14.29	1.23**	14.42
Accounting/bookkeeping	1.17	14.30	1.18	14.31
Financial service use (1 = yes, 2 = no)				
Transaction services	1.58	19.23	1.62	17.98
Cash management services	1.94	8.82	1.96	7.58
Credit services	1.97	6.38	1.96*	7.58
Trade services	1.86	13.33	1.91	10.64
Brokerage services	1.95	8.21	1.97	6.42
Used trade credit	1.38	18.97	1.37	17.83
If yes: % of purchases	69.11	1,226	71.14	1,160
Number of trade credit suppliers	25.37	4,442	19.06	2,832
% offering cash discount	20.51	1,199	28.00*	1,338
% balance paid after due date	31.67	1,622	29.02	1,504
Length of discount period	13.97	537	14.20	606
Amount of discount	1.46	125	2.41	70.5

*Statistically significant based on Wilcoxon nonparametric linear rank test @ p< .05
**Statistically significant based on Wilcoxon nonparametric linear rank test @ p< .01

Table 4. Creditworthiness

Item	Metro		Rural	
	(Weighted Mean)	(Std. Dev.)	(Weighted Mean)	(Std. Dev.)
Dun & Bradstreet score (1 = low risk, 5 = high risk)	3.01	38.72	2.93*	36.04
Denied trade credit (1 = yes, 2 = no)	1.94	9.12	1.96	6.93
Bankrupt in past seven years (1 = yes, 2 = no)	1.95	6.07	1.97	5.69
Delinquent on business obligations (1 = yes, 2 = no)	1.32	34.15	1.26*	27.62
Didn't apply for mortgage loan fearing denial (1 = yes, 2 = no)	1.76	16.65	1.79*	14.96

*Statistically significant based on Wilcoxon nonparametric linear rank test @ $p < .05$

Credit Counseling and Mortgage Termination by Low-Income Households

Valentina Hartarska and Claudio Gonzalez-Vega *

Abstract

Published research on credit counseling and mortgage termination is surprisingly scarce, despite substantial growth in this industry. While the purpose of counseling is to help low-income borrowers to handle better debt, and thus prevent default, counseling could also improve these borrowers understanding of their financial positions and thus affect prepayment. This paper shows that evaluations of counseling programs with a narrow focus on default may miss an important effect that counseling may have on prepayment. We use a competing risks framework to study the effects on both default and prepayment of a counseling program implemented in several Mid-West states. Our results indicate that the default hazard was not lower for the graduates of the counseling program but that the prepayment hazard was higher. Overall, counseling seems to affect lenders' profits but the net effect should be evaluated both in terms of prepayment and default.

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Credit Counseling and Mortgage Loan Termination by Low-Income Households

1. Introduction

Many lending initiatives, usually termed "affordable lending" promote lending to low-income households by using flexible underwriting guidelines and new mechanisms for risk mitigation such as counseling. The ostensible purpose of credit counseling is to help low-income borrowers estimate better the amount of debt they would be able to service and, thus, prevent default. Counseling, however, improves low-income borrowers' understanding of their financial position as well as their understanding of mortgage loan markets and, therefore, it may have an affect on borrower prepayment.

Counseling is a growing industry but little is known about its effectiveness. Previous studies have focused primarily on homeownership, default and delinquency, but none have explored how credit counseling may simultaneously affect both default and prepayment. Understanding how counseling may affect prepayment is important, because the cost of a mortgage loan includes a significant premium to compensate for prepayment risk. Some evidence suggests that low-income households have higher default hazards but lower prepayment hazards, perhaps because their propensity refinance is dampened by income and collateral constraints and because, financially, these households are less endowed and less sophisticated (Archer, Ling and McGill*,* 1996; Peristiani, Bennett, Monsen *et al.,*1997; Goldberg and Harding, 2003).

This paper studies the effect of counseling on both prepayment and default by adopting a competing risks approach to mortgage termination. Using data on a counseling program implemented in several, mainly Mid-West, states during the 1991-2000 period, we explore the idea that counseling affects borrower behavior and that counseled borrowers may default less often but may also prepay more often than non-counseled borrowers. The results suggest that the counseling program examined indeed graduates borrowers who differ in both prepayment and default patterns. The findings also show that a narrow focus on the effects of counseling on default may provide misleading results on the overall effectiveness of various programs.

2. Discussion of the literature

At present, there is no systematic body of research that clearly demonstrates that counseling influences default on mortgage loans (McCarthy and Quercia, 2000). Studies of counseling programs in California in the mid- and late-1970s show both positive and no effect on homeownership rates, and a study of counseling programs in Detroit shows long–term negative effects of counseling on default (Mallach, 2001). There is evidence that credit counseling improves the subsequent use of credit, but this result cannot be readily extended to home purchase counseling, which often deals with both the housing and the financing decisions (Mallach, 2001; Ellienhausen, Lundquist, and Staten, 2003).

Counseling programs vary by method of delivery, desired outcomes, characteristics of the counselors (stake in the transaction and qualifications), and program content. In terms of content, credit counseling programs usually include topics on credit issues and financing including financing of a home. Homeownership counseling programs include these topics but may add topics such as finding a home and maintaining the property. This complexity requires that the research methodology be adjusted to address the specific characteristics of each program.

The lack of published research is also due to data scarcity. In 2000, Price Waterhouse Coopers abandoned a project to study the effectiveness of counseling after a feasibility study concluded that lenders either do not collect or collect very limited data about borrowers who have undergone counseling (Mallach, 2001). Data availability is an important issue because even when such data are available, they are often proprietary and, thus, less accessible to external researchers. In addition, since many affordable loan programs require counseling as part of the loan qualification requirement, is it hard to find an adequate control group.

This is one of the challenges that Hirad and Zorn (2002) encounter in their, to date, most comprehensive study on the effectiveness of homeownership counseling. They use a sample of 40,000 mortgages originated under the Freddie Mac's Affordable Gold program to assess how pre-purchase homeownership counseling affects delinquency rates. As a quasi-control group they use loans in the Affordable Goal loans that qualified for exemption from counseling. The qualities of these borrowers that made them qualify as an exception may, the authors state, make them somewhat different from the counseled borrowers. Hirad and Zone attempt to control for this endogeniety by using a nested logit model and find that after this correction counseling still decreases the 90 day delinquency rate and that different type of counseling vary in their effectiveness.[1] However, after these adjustments the study fails to confirm the effectiveness of some types of counseling like individual in person counseling and home-study counseling.

Hirad and Zorns' study focuses on delinquency and uses a logit model, where the explanatory variables are controls for counseling, borrower characteristics, and loan and property characteristics. Quercia and Watcher (1996) suggest that innovative methodology to study the effectiveness of counseling would come from recent developments in the literature on default. The modern literature on default views default as the exercise of an option.

According to option-based theory, the decision to terminate the mortgage (through default or prepayment) is a purely financial decision, independent of the housing decision. The value of a mortgage loan consists of the present value of scheduled payments by a borrower and the value of the options granted to the borrower to terminate the mortgage either by prepayment or default. When deciding on how to act on the loan obligation, a borrower faces several choices. The borrower has the choice to (1) make the payment on the loan and continue in good standing as a debtor, (2) pay in full the remaining balance on the loan, by refinancing (prepayment, or call option), or (3) surrender the house to the lender in exchange for cancellation of the debt (put, or default option). Thus, prepayment and default are two actions that borrowers undertake to increase their wealth.

Furthermore, a series of papers developed the theoretical arguments that emphasize the importance of the *jointness* of the prepayment and default options (Kau, Keenan, Muller *et al.,* 1992 and 1995). At least partially, this development was motivated by the observation that default rates predicted by the option theory differed from observed default rates. Failure to exercise the default option, researchers reasoned, could indicate that borrowers may expect that this option could have even higher value in the future. Moreover, borrowers may not exercise the default option when it is in-the-money because they may expect that in the future the prepayment option would be more valuable.

[1] Without adjustment for endogeniety, Hirad and Zorn (2002) find that delinquency rates were the lowest in individual homeownership counseling programs, followed by classroom counseling, with telephone counseling being least effective.

As a result of these theoretical developments, mortgage termination is now being specified in a competing risks framework, where the values of the prepayment and default options are included and where borrower heterogeneity, trigger events and transaction costs are controlled for (Deng, 1997; Deng and Gabriel, 2002; Deng, Quigley and Van Order, 2000; Clapp, Goldberg, Harding *et al.,* 2001; Pavlov, 2001; and Archer, Ling and McGill, 2003).

A competing risk approach is appropriate to study the effect of credit counseling because counseling may improve the borrowers' level of financial sophistication, as it introduces concepts such as the present value of money and annualized interest rates. As interest rates and property values change, borrowers who have undergone counseling may have a better understanding of how these changes affect the value of their loan obligations. This better knowledge may improve the borrowers' ability to "price" their options. At the same time, counseling may improve creditworthiness of borrowers who already are financially sophisticated and thus more likely to prepay. If this is the case, lenders need to be aware that the potential benefit of lower default rates must be weighted against the potential cost of higher prepayment rates. Thus, exploring its effects on both prepayment and default will most fully account for the consequences of counseling.

3. Description of the credit counseling program

The Community Mortgage Loan Program studied here was part of a larger Community Centered Banking program, organized by a major bank in Columbus, Oh to fulfill this bank's CRA requirements and provide financial services to underserved communities. This larger program targeted low-to-moderate income households who did not routinely use the banking system and who typically were declined loans. The objectives of the Community Centered Banking program were to improve the integration of the financial products offered in a community and to enhance opportunities available to low-to-moderate income households. The program was organized in collaboration with Community Churches and a local consulting firm with experience in implementing community outreach programs.[2] Potential clients were approached through a series of seminars organized by the Community Churches. Through this program, low-income households gained access to a full range of banking services—checking and savings accounts, student and consumer loans, and educational services.

As the bank learned more about the financial needs of the target population, it identified a substantial need for mortgage loans and the *Community Mortgage Loan Program* (CML) was initiated in 1992. The purpose of this program was to provide cost-efficient mortgage loans to low-income households, in a fashion profitable to the bank. The program was designed for this specific market. Borrowers could get mortgage loans for up to $75,000 with a down payment of the lesser than 5 percent of the loan or $1,000 down payment with gifts and grants accepted as alternative source of down payment.[3] The bank offered eased credit restrictions, one percent origination fee, no discount points, the bank could also negotiate to pay mortgage insurance, and when applicable, it would pay for counseling services. To cover its costs the bank charged interest rate of 150 points above the Fannie Mae 60 days average rate on 80% LTV conforming loans.

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[2] The community churches and the outreach consulting firm collaborated not only on the CCB project where the bank was their third partner but also in other areas such as education, employment, alcohol and substance abuse, healthcare, community relations and crime. This collaboration relied on and improved the social capital in the community and helped the bank recruit more creditworthy borrowers (Hartarska and Gonzalez-Vega, 2003).

[3] In 12 cases, the bank granted loans bigger than $75,000 to customers recruited through the Community Churches.

At the beginning of the program, counseling was not available in all regions, or at all times in areas where the bank was organizing seminars and offering its services and therefore some borrowers received counseling and some did not. In fact, according to the bank representatives counseling services were offered quite randomly prior to 1996 because of the lack of systematic agreements with counsel providers and because of various pressures to fulfill lending targets. Since 1996 Fannie Mae became a partner in the program by offering to buy non-delinquent loans seasoned for at least three years. Since 1996, counseling became an obligatory part of the qualification for mortgage loans with this program. All borrowers recruited through the seminars organized in collaboration with Community Churches were required to meet with a counsel provider at lest once.

Counseling was provided by the Consumer Credit Counseling Services (CCS), an organization with several decades of experience. They offered a product based on proximity to, and knowledge of, the potential clientele. To address the specific needs of each borrower, the amount of counseling was individually determined. Each potential borrower provided preliminary information, on the basis of which a counselor determined how many sessions each person had to attend. Counseling included some traditional topics such as improving spending habits, correcting problems on non-sufficient funds checks, improving the use of credit, debt consolidation. Potential clients discussed with a counselor where they lived, whether they have changed job or income. Depending on the client, counseling could last sometimes up to 2 years.[4]

Some parts of the counseling program were different from the traditional counseling offered by the CCS. On recommendations of the consulting firm that helped bring together Community Churches and the bank, counselors focused on the cash flows of potential borrowers. Potential borrowers learned how to keep track of their living expenses, measure their level of debt, and calculate whether the expected mortgage loan could be sustainable. Graduation from the counseling program was granted only to those participants who, given an interest rate and a loan amount, could generate zero or positive cash flow, based on a thorough verification and calculation of their actual living expenses and debt. Loan amounts adjusted by these criteria do not always correspond to those resulting from the standard financial ratios used as a screening device.[5] Households who cannot become homeowners did not graduate from the counseling program and were not able to get mortgage loan. Graduation made borrowers eligible to apply for a loan at the bank and the bank had a final say in who is granted a credit and who is denied.

The Community Mortgage Program also combined counseling with some financial assistance. If the borrower could not afford the lesser than five-percent or $1,000 down payment, she was granted a consumer loan to make this possible. The extra debt was accounted for in the calculation of the household cash-flow constraints.

The expertise of the counselors, combined with a conservative approach to maximum sustainable debt estimation could be important advantages of counseling in reducing defaults. Since the program improved low-income households understanding of the way mortgage loans affect their welfare, counseling may have affected prepayment behavior as well.

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[4] All counseling was pre-purchase counseling, the focus was on the credit side of the mortgage loan and counseling did not include topics on responsibilities of homeowners.

[5] In the absence of credit scoring methods, the estimation of standard debt ratios and borrower net worth was among the most important determinants of creditworthiness, as perceived by the bank. The banks started using credit scores only in 1998 and that is why credit scores cannot be used in this analysis.

4. Methodology

We study the prepayment and default behavior of counseled and non-counseled borrowers in a competing risks framework. Prepayment and default are two actions driven by the value of the underlying prepayment (call) and default (put) options that borrowers undertake in order to increase their wealth. Since by exercising one option the borrower gives up the other, the extent to which one option is in the money affects the exercise of the other. For instance, the probability of prepayment is a function of the extent to which the default option is in the money. This jointness of the two options is captured well in the competing risks framework.

The option-based theory stipulates that when a payment on the mortgage loan becomes due, depending on the value of the put and call options, and given transaction costs and trigger events, the borrower decides whether to default on the loan, prepay or remain current. Let default and prepayment be termination events, and let loans that remain current be observations that were censored at the time of data collection. To develop the competing risks model, we first consider a hazard function for default and a hazard function for prepayment defined as

$$\lambda_j[t; X(t)] = \lim_{h \to 0} h^{-1} P(t \leq T < t + h \mid J = j) \qquad \text{for } j=1,2 \tag{1}$$

where j=1 for default and j=2 for prepayment, T is continuous termination time, $x(t)$, $t \geq 0$ is a vector of possibly time-dependent covariates, $X(t) = \{x(u) : 0 \leq u < t\}$, that is $X(t)$ is the history of the covariates prior to time t. Here $\lambda_j[t; X(t)]$ represents the instantaneous rate of termination (by default or by prepayment), given $X(t)$. If only one termination type can occur, that is, if the borrower could either prepay or default, then

$$\lambda[t; X(t)] = \sum_{j=1}^{2} \lambda_j[t; X(t)] \tag{2}$$

Applying the specification of the Cox model, the termination specific hazard function is

$$\lambda_j[t; X(t)] = \lambda_{0j}(t) \exp[Z(t)'\beta_j] \qquad \text{for } j=1,2 \tag{3}$$

Here, $Z(t)$ is a p derived vector of possibly time-varying covariates defined as a function of $X(t)$, where $X(t)$ is left continuous with right hand side limits; the baseline hazard $\lambda_{0j}(t)$ and the regression coefficients β_j can vary arbitrary over the termination types, that is, the baseline hazard of default and prepayment and the estimated coefficients on are allowed to be different as required. The overall survivor function S (which is nothing else than one minus the *cdf*) is defined as

$$S[t; X(t)] = \exp - \sum_{j=1}^{2} \int_0^t \lambda_{0j}(u) \exp[Z(u)'\beta_j] du \tag{4}$$

The individual *pdf* for each termination type is

$$f_j[t; X(t)] = \lambda_j[t; X(t)] S[t; X(t)] \qquad \text{for } j=1,2 \tag{5}$$

and the overall density function is

$$f[t;X(t)] = f_1[t;X(t)] + f_2[t;X(t)] \tag{6}$$

If t_{ji}<… <t_{jki} denote the k_j time of type j termination and Z_{ji} denote the regression be function for the individual that terminated the loan at t_{ji}, then the Loglikelihood to be maximized is

$$LogL(\beta_1, \beta_2) = \sum_{j=1}^{2} \left\{ \sum_{i=1}^{k_j} \left[\exp[Z_{ij}(t)\beta_j] - \sum\nolimits_{l \in R(t_{ji})} \exp[Z_l(t_{ji})'\beta_j] \right] \right\} \tag{7}$$

where β_j for j=1,2 are the estimated coefficients and $R(t_{ij})$ is the set of all individuals who have not terminated and are still under observation just prior to t. The baseline hazard is eliminated and not estimated in this model but it is allowed to vary by termination type, that is, is can be different for prepayment and for default. [6]

This paper uses the specifications introduced in Deng, Quigley and Van Order (1997 and 2000) and used in studies on mortgage terminations (Ambrose and Capone, 2000; Pavlov, 2001) to measure of the influence of the put and call options on mortgage termination. The first variable measures the probability that the put option is in-the-money, that is, the probability that defaulting has value, PROBNEQ is defined as:

$$\text{PROBNEQ}_{i,k_i} = prob(E_{i,k_i} < 0) = \Phi\left(\frac{\log V_{i,m_{j,\tau_i+k_i}} - \log M_{i,k_i}}{\sqrt{w^2}} \right) \tag{8}$$

where E_{i,k_i} is the equity in the house for the i^{th} individual, evaluated k periods after origination, $\Phi(.)$ is a cumulative standard normal distribution function; $V_{i,m_{j,\tau_i+k_i}}$ is the value of the present value of the outstanding loan balance at $m_{\tau_i+k_i}$ market interest rate, w^2 is the estimated variance from repeat (paired) sales, by state, provided by the Office of Federal Housing Oversight (OFHEO). Here, M_{i,k_i} is the market value of property, purchased at cost C_i at time τ_i and evaluated k_i months thereafter is

$$M_{i,k_i} = C_i \left(\frac{I_{j,\tau_i+k_i}}{I_{j,\tau_i}} \right) \tag{9}$$

where the term in parenthesis follows a log-normal distribution and I_{j,τ_i} is an index of house prices by state j, at time τ_i. The higher the value of PROBNEQ, the higher the probability that the equity in the house is negative and the more profitable it is to default.

[6] For more detail see Kalbfleisch and Prentice (2002) and Crowder (2001).

To study whether the call option influenced prepayment, this paper uses PREPAY, which is equal to one minus the ratio of the present value of the unpaid mortgage balance at the current market interest rate $m_{\tau_i + k_i}$, relative to the value discounted at the contract interest rate. That is

$$PREPAY_{i,k} = 1 - \frac{V_{i,m_{j,\tau_i+k_i}}}{V^*_{i,r}} \tag{10}$$

where

$$V_{i,m_{j,\tau_i+k_i}} = \sum_{t=1}^{TM_i - k_i} \frac{P_i}{(1 + m_{\tau_i + k_i})^t} \tag{11}$$

$$V^*_{i,r_i} = \sum_{t=1}^{TM_i - k_i} \frac{P_i}{(1 + r_i)^t} \tag{12}$$

and where P_i is the monthly payment in principal and interest and r_i is the contract interest rate. Positive values would indicate that the option is *out-of-the-money*, that is, it is not to the borrower's advantage to prepay; the option will move *in-the-money* as it becomes negative because negative values indicate that contract rate is greater than the market rate and it will be more profitable to refinance.

Other time-variant events that affect termination are divorce and shocks to income (Quigley and Van Order, 1995; Elmer and Seelig, 1999). These have been characterized as trigger events because they may trigger termination through either default or prepayment. We control for this event through a time-variant dummy SHOCK.

The time-invariant covariates included are value of the loan, monthly payment and value of the house which serve as a proxy of borrower income level and wealth; mortgage insurance paid by the bank, property type (single unit, two-unit), origination year and loan-to-value ratio at time of origination, which serves as a proxy for the down payment.[7]

This specification controls for the characteristics of the loan contract, property type and shock events. A significant coefficient on the dummy for counseling on both prepayment and default, after controlling for these variables, would indicate that lenders should not ignore the effect of counseling on prepayment.

We define loans in default as loans for which foreclosure took place, loans tied up in bankruptcy procedures and/or loans for which a loss was realized, as well as loans coded as DIL, (dead-in-lieu or foreclosure), and PRS (presale/short sale). Default is recorded at a time when these loans became 90 days overdue. Regarding prepayment, the information available is less detailed. The bank has not collected information on the reason for prepayment—refinancing or moving. This may affect the results. Clapp, Goldberg, Harding *et al.* (2001) report that prepayment due to refinancing and prepayment motivated by a move are affected by different factors.

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[7] Monthly pay and loan amount are not necessarily equivalent and are both included because although most of the loans were 30 year fixed rate loans, on occasion the bank granted fixed-rate loans for 10, 15, 20 or 25 years. No information on these outliers was available, however.

5. The Data

The complete dataset consists of 1,338 loans originated from 1992 to 2000 to borrowers mainly in Ohio but also to few borrowers from Florida, Indiana, Kentucky, Michigan, and West Virginia (Table 1). Thirty two observations were deleted because origination data were incomplete, thus the final number of loans is 1306. The sample of loans originated prior to 1996, when counseling was offered in some and regions and period, contains 919 loans. Of them, 410 are to counseled borrowers and 509 are to non-counseled clients (Table 1). During the period from 1996 to 2000, when counseling was obligatory for everybody recruited through the Community Mortgage Loan Program, the bank originated 387 loans.

Repayment records in the sample expand up to nine years with most loans still outstanding. The characteristics of the portfolio presented in Table 2. It is organized in two panels, with Panel A presenting data for the complete portfolio and Panel B presenting data for all loans that were originated prior to 1996. Clearly, using only loans originated prior to 1996 is better because the relatively random availability of counseling makes the group of non-counseled borrowers an appropriate control group for two reasons. First, counseling was not mandatory during the period so counseling was done somewhat random, and second, these loans were given in relatively similar economic conditions (Graph 1 and Graph 2).

This data are interesting to analyze because counseling is often made obligatory for some low-income categories of borrowers as a precondition of getting a mortgage loan and there are rarely adequate control groups. Analysis of sample of loans originated prior to 1996 and the portfolio with loans originated after 1996 allows to study not only whether counseling affects termination but also what are the consequences of making counseling mandatory to everybody in a population of low-income borrowers, who do not use the banking system and who may be categorized as less creditworthy.

Comparison of the characteristics of the loan performance of the two groups (Table 2) reveals that their prepayment patterns prior to 1996 do not differ while default is slightly higher for the counseled borrowers. If non-counseled borrowers are compared to all counseled borrowers including those who received a loan after 1996, when it became mandatory to have counseling, then counseled borrowers have lower both default and prepayment rates.

Table 3 presents definition of the variables used in the analysis. The database does not contain information of borrower characteristics, which have been found to be related to termination. Loan amount, house value and monthly payment and LTV at time of origination are used to proxy the level of housing that each household could afford and may, to a limited extent, proxy for household income and wealth. Loan-to-value at origination can be used to control for the amount of down payment and as argued by Pavlov (2001) for borrower heterogeneity as he includes LTV in the group of variables that proxy borrower heterogeneity.

Table 4, presents the means and standard errors of the variables in the portfolio by various groups—all loans, loans originated prior to 1996, counseled borrowers and non-counseled borrowers. The data reveal that the two groups are very similar. As expected, the probability of negative equity has increased at the time of default for all groups. Counseled borrowers had higher values of the probability of negative equity at both time of origination and at time of termination. As expected, loans were repaid when the value of the prepayment option was in-the-money, as indicated by the negative sign of this variable at termination. Compared to non-counseled borrowers, counseled borrowers started with higher value of the prepay option.

A trigger event was the reason for default for half of the counseled borrowers, while only thirty percent of the non-counseled borrowers reported a shock event as a reason for default. This difference may be due incorrect reporting of the reason for delinquency, as it may be that counseled borrowers were more involved in the program and more willing to reveal why they are defaulting on the loans as opposed to non-counseled borrowers who did not interact with counselors and were less comfortable sharing the reasons of their default. A larger percentage of the non-counseled borrowers qualified for a loan without mortgage insurance (9.7 percent, versus 5.9 percent). Mortgage loans were used to buy mainly single family houses, with counseled borrowers buying slightly higher proportion. Perhaps because of this both loan amount and house values are slightly higher for the counseled borrowers. On average they also paid slightly lower down payment.

The data on origination indicates how the program progressed as the share of the non-counseled borrowers decreases while that of counseled increases. Overall, the differences in the loan and property characteristics of the two groups are every similar and indicate that the non-counseled borrower could serve as a reasonable control group.

6. Discussion of Results

The results show that counseling must be evaluated in terms of its effects on both prepayment and default. Borrowers who graduated from the counseling program did not necessarily have lower default hazard but they do seem to have a higher prepayment hazard.

Model 1 in Table 5 presents the results of a model which uses data for all loans prior to 1996. Although counseled borrowers did not default less than non-counseled borrowers (the coefficient on the default hazard is insignificant), they did prepay more-often than non-counseled borrowers.

The same result is obtained with data from the complete portfolio in a Model 2 in Table 5, which also includes dummies for years of origination prior to 1996. Counseled borrowers still prepay more often but this result is attenuated, as the coefficient is now significant only at 10 percent (p value is 0.09). The effect of counseling on prepayment seems to be affected by the fact that all borrowers recruited though church seminars since 1996 were asked to go through counseling. In this model, counseled borrowers default less often but the coefficient is not statistically significant.

Results also indicate that the competing risks framework is appropriate to study mortgage termination by low-income households. As expected, and in both models, default is affected positively and significantly by the probability of negative equity and by the value of the prepayment option. Also as expected, and in both models PREPAY affects significantly prepayment, that is, the more negative PREPAY is, the more profitable it is to prepay. As, expected, the sign on PROBNEQ is negative in Model 2 but it is not significant. Surprisingly, this sign is positive and significant in Model 1, indicating that borrowers prepaid when the probability that their equity was negative was high. This result could indicate that low-income borrower's reputation was so important that they might have taken a financial loss (by selling the house or refinancing) and prepaying even if defaulting for pure financial considerations would have been wealth increasing.

As expected, the variable that approximates the effect of trigger events is significant in the default hazard in both specifications, and it is even negative and significant in the prepayment hazard of Model 2. Borrowers who bought single family or two-family houses were less likely to default but property type did not affect prepayment hazard.

For the low-income borrowers who participated in this program, larger loan size increased the chance that the mortgage would have been terminated. The value of the property
did not affect prepayment but borrowers who bought higher valued houses had lower default hazards. Loans with higher monthly payment were less likely to be prepaid but more likely to become in default. It is widely accepted that loans with higher LTV (smaller down payment) are more risky. The results show that this was not the case for the low-income people in the portfolio. On the contrary, borrowers with higher LTV have lower default hazards. Such result is not unusual in lending to low-income households. MFIs have discovered that in low-income communities, the poorer the borrower, that is the less collateral he/she has, the more important the reputation becomes and this translates into fewer defaults in the poorest of the poor (ref with the most prestigious journal).[8]

6. Conclusions

Published research on credit counseling and mortgage termination is surprisingly scarce, despite substantial growth in this industry. Counseling is usually an obligatory requirement for the low-income to qualify for a mortgage loan, it is expensive, and it is important to understand how it affects mortgage termination. This paper shows that evaluations of counseling programs with a narrow focus on default miss important an effect that counseling may have on prepayment. We use a competing risks framework to study the effects on both default and prepayment of a counseling program implemented in several Mid-West states. The paper shows that the default hazard was not lower for the graduates of the counseling program but that the prepayment hazard was higher. Overall, counseling seems to affect lenders' profits and this effect should be evaluated both in terms of prepayment and default hazards and the higher prepayment hazard should be accounted for through an adequate prepayment premium.

[8] Borrowers in our sample are less wealthy, with the average loan amount of $46,000, than borrowers in the comparable study of the effect counseling on delinquency by low income borrowers conducted by Hirad and Zorn, (2002), where the average loan for comparable period (1993-1998) was $94,000.

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Table 1.Geographic distribution of the loans by year [a]

Year	OH	FL	IN	KY	MI	WV
1992	100[b]					
1993	100					
1994	100					
1995	89.1	3.9	2.3	0.0	1.6	3.1
1996	86.5	1.9	1.9	5.8	0.0	3.8
1997	92.0	0.9	1.8	1.8	0.0	3.6
1998	89.4	2.1	0.0	4.3	1.1	3.2
1999	93.1	1.4	1.4	2.8	0.0	1.4

[a] all loans to non-counseled borrowers are to borrowers from Ohio.
[b] percentage of loans originated in the current year.

Table 2. Description of the Portfolio.

Panel A: All loans in the portfolio

Loan Status	Non-Counseled		Counseled		Total	
	Number	%	Number	%	Number	%
In Default	42	8.3	55	5.6	97	7.4
Prepaid	81	15.9	124	12.7	205	15.7
Current	386	75.8	800	81.7	1004	76.9
Total	509	100	979	100	1306	100

Panel B: Loans originated prior to 1996

Loan Status	Non-Counseled		Counseled		Total	
	Number	%	Number	%	Number	%
In Default	42	8.3	38	9.3	80	8.8
Prepaid	81	15.9	63	15.4	124	13.6
Current	386	75.8	309	75.4	705	77.6
Total	509	100	410	100	909	100

Table 3. Variable definition

Variable Name	Description of the Explanatory Variables
COUNSELED	1 if the borrower was counseled, zero otherwise
PROBNEQ	Probability that the borrowers' equity is negative (as in Deng *et al.,* 2000)
PREPAY	1 minus the ratio of discounted value of the remaining mortgage payment at current market rate to the discounted value of the remaining mortgage payment at the contract interest rate
LTV	Loan-to-value ratio at time of origination
SFHOUSE	Property is a single unit house
DFHOUSE	Property is a double unit house
SHOCK	1 if the borrower has indicated that a shock event has caused the delinquency, 0 if no reason was indicated
LAMOUNT	Loan amount
HVALUE	House value at time of loan origination
MPAY	Monthly payment on the loan (principal and interest, does not include insurance and taxes)
NMI	1 if the loan did not need/have mortgage insurance
ORIGIN92	The mortgage was originated in 1992
ORIGIN93	The mortgage was originated in 1993
ORIGIN94	The mortgage was originated in 1994
ORIGIN95	The mortgage was originated in 1995

Table 4. Means and standard errors of the regression variables by groups

	All loans (prior to 1996)	Non-counseled	Counseled (prior to 1996)	Counseled (all loans)	All loans
COUNSELED[a]	0.446				0.610
	(0.497)				(0.488)
PROBNEQ	0.386	0.261	0.588	0.629	0.427
	(0.347)	(0.243)	(0.398)	(0.401)	(0.370)
PROBNEQ[b]	0.520	0.361	0.696	0.738	0.575
	(0.330)	(0.279)	(0.294)	(0.261)	(0.327)
PREPAY	-0.036	0.021	-0.1011	-0.131	-0.073
	(0.101)	(0.053)	(0.102)	(0.083)	(0.105)
PREPAY[b]	-0.161	-0.115	-0.219	-0.209	-0.172
	(0.101)	(0.068)	(0.105)	(0.093)	(0.096)
REASON[c]	0.400	0.309	0.500	0.491	0.412
	(0.493)	(0.468)	(0.507)	(0.505)	(0.495)
NMI	0.077	0.097	0.059	0.165	0.134
	(0.267)	(0.296)	(0.235)	(0.372)	(0.341)
SFHOUSE	0.929	0.917	0.978	0.961	0.943
	(0.257)	(0.276)	(0.220)	(0.194)	(0.233)
TFHOUSE	0.042	0.047	0.036	0.031	0.038
	(0.202)	(0.213)	(0.186)	(0.174)	(0.190)
LAMOUNT	44,237	43,295	45,692	48,806	46,326
	(11,242)	(10,619)	(12,192)	(14,806)	(13,477)
HVALUE	48,204	47,226	49,083	52,693	50,564
	(12,223)	(12,094)	(12,244)	(15,561)	(14,449)
MPAY	349.969	326	379	394	370
	(9.852)	(81)	(106)	(119)	(112)
Log (RINCIPAL)	10.657	10.640	10.680	10.731	10.696
	(0.305)	(0.280)	(0.372)	(0.347)	(0.328)
Log(HVALUE)	10.746	10.727	10.762	10.823	10.787
	(0.287)	(0.275)	(0.301)	(0.329)	(0.311)
Log(MPAY)	5.814	5.752	5.982	5.932	5.863
	(0.316)	(0.280)	(0.328)	(0.343)	(0.336)
LTV	91.843	91.883	92.488	91.636	91.728
	6.434	(5.896)	(7.898)	(8.136)	(7.696)
ORIGIN 92	0.214	0.326	0.077	0.039	0.151
	(0.411)	(0.469)	(0.266)	(0.194)	(0.358)
ORIGIN 93	0.366	0.529	0.179	0.089	0.258
	(0.482)	(0.499)	(0.379	(0.285)	(0.438)
ORIGI N 94	0.249	0.140	0.426	0.218	0.183
	(0.433)	(0.347)	(0.495)	(0.413)	(0.387)
ORIGIN 95	0.168	0.020	0.324	0.160	0.123
	(0.374)	(0.044)	(0.468)	(0.413)	(0.329)

[a] all values are at origination unless indicated otherwise
[b] values at termination
[c] values at default

Table 5. Maximum likelihood estimates of a competing risks model of mortgage prepayment and default

	Model 1		Model 2	
	Prepay	Default	Prepay	Default
COUNSELED	0.817	0.255	0.346	-0.291
	(4.31)	(0.91)	(1.67)	(0.92)
PROBNEQ	2.11	7.062	-1.195	8.824
	(1.91)	(4.54)	(1.11)	(6.55)
PREPAY	-13.953	18.411	-23.255	18.488
	(-7.28)	(5.04)	(-11.37)	(6.05)
NMI	-1.073	-0.432	0.153	-0.227
	(2.76)	(0.74)	(0.41)	(0.38)
SHOCK	-0.549	1.678	-0.654	1.793
	(1.45)	(6.99)	(2.10)	(8.23)
LTV	-0.078	-0.667	-0.006	-0.706
	(1.45)	(3.08)	(0.11)	(3.23)
SFHOUSE	-0.129	-1.822	0.060	-1.826
	(-0.17)	(2.91)	(0.06)	(3.05)
TFHOUSE	0.189	-1.552	-0.329	-1.966
	(0.21)	(1.85)	(0.31)	(2.30)
LAMOUNT	11.214	33.032	18.359	40.446
	(3.92)	(1.86)	(2.499)	(2.33)
HVALUE	-2.007	-42.107	0.265	-44.076
	(0.78)	(2.45)	(0.14)	(2.51)
MPAY	-8.693	10.338	-18.217	3.649
	(4.90)	(3.30)	(9.53)	(1.75)
ORIGIN92			-8.499	-2.776
			(16.46)	(5.56)
ORIGIN 93			-6.877	-2.034
			(15.43)	(4.39)
ORIGIN 94			-5.089	-0.790
			(14.07)	(2.08)
ORIGIN 95			-4.040	-0.385
			(9.96)	(-1.00)
Log likelihood	-1967		-2552.987	
No. observations	919		1306	

t-values are in the parentheses.

Figure 1. Fannie Mae 60 days averages for 30 year fixed rate mortgages.

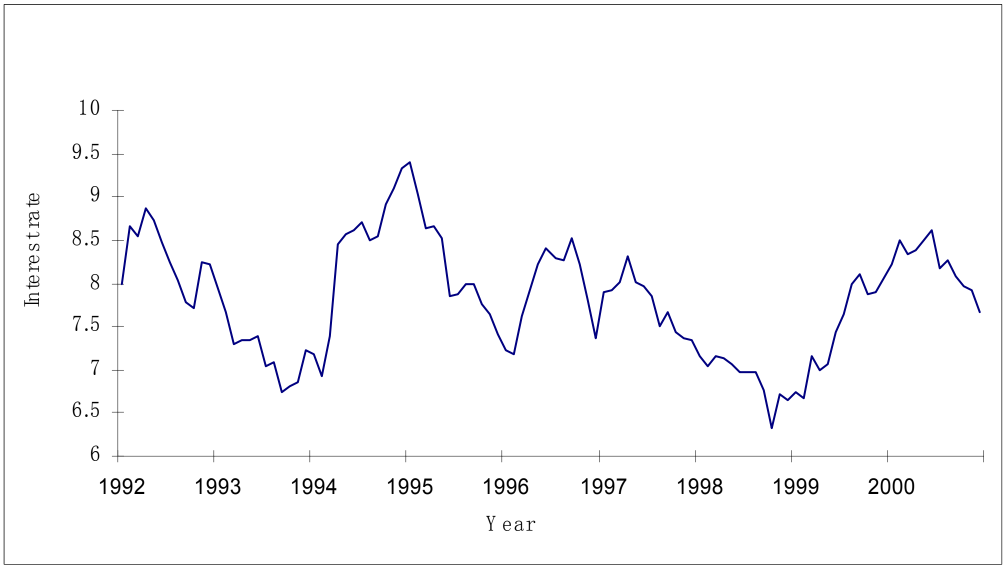
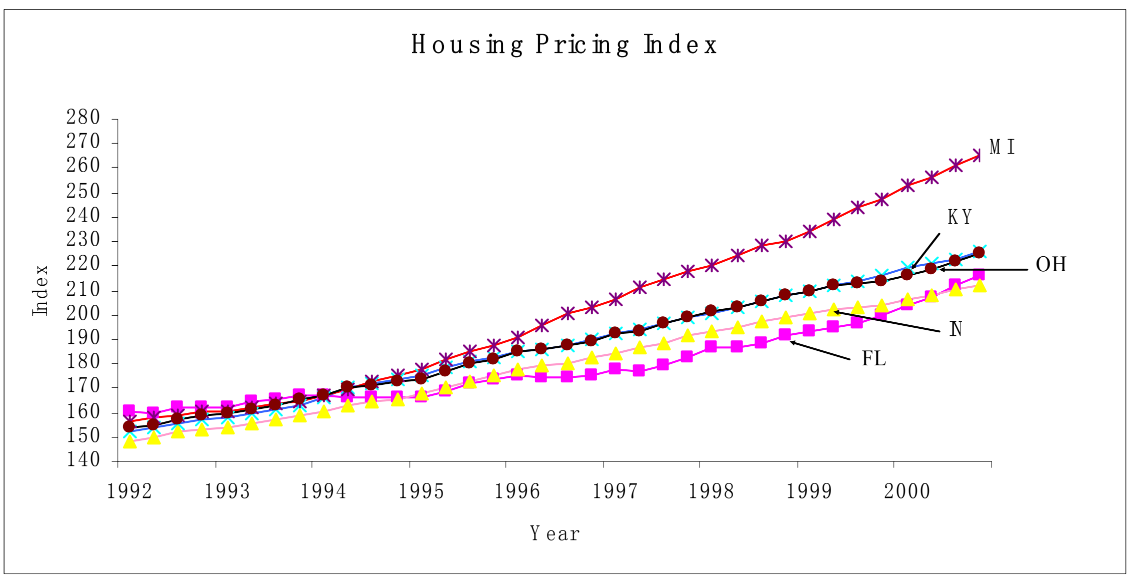


Figure 2. Housing price index by state.



Risk Sharing and Incentives
with Crop Insurance and External Equity Financing

Sangtaek Seo, David J. Leatham, and Paul D. Mitchell*

Abstract

Farmers have increasingly been procuring external equity financing through either written or verbal business arrangements. Passage of the Agricultural Risk Protection Act in 2000 has resulted in widespread adoption of crop insurance among farmers. Crop insurance changes farmers' production decisions, so that investors providing external equity may want to adjust the equity financing contract to account for these changes. This paper uses a principal-agent model to determine optimal risk sharing and incentives under crop insurance and external equity financing. Results show that with the introduction of crop insurance, the investor's optimal equity financing contract requires that the farmer bears more risk in order to have the incentive to work hard.

Key words: risk sharing, incentives, crop insurance, equity financing, principal agent model.

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Risk Sharing and Incentives with Crop Insurance and External Equity Financing

Arrangements such as land leases, partnerships and other corporations, and vertical integration have been the traditional channels through which farmers have obtained external equity, i.e. equity capital procured from the non-farmers or other sources than retained earnings. Sharecropping is probably the most common use of external equity (Allen and Lueck). Based on the 1988 Agricultural Economics and Land Ownership Survey, Canjels reported that almost one-third of all leased acres were sharecropped in 1988. In many of these arrangements, the landlord provides the land and/or input costs for farming and shares the output with the farmer. Partnerships and other forms of corporations comprised 10% of farms in 1997 and these farms accounted for 48% of total farm product sales (USDA-NASS). The members of the partnership and corporation might share the output or dividends according to the investment share or the share of the operating costs. To use external equity, a farmer needs a contract in verbal or written form with the investor providing the external equity. For example, 90% of surveyed California wine grape farmers used contracts in 1999, with 70% using written contracts only, 11% using oral contracts only, and 9% using both contract types (Goodhue, Heien, and Lee). These contracts typically specify the investment share, input use, and/or output shares. The investor may provide additional economic incentives to derive the best effort of the farmer.

Farmers have several risk management alternatives available, such as crop insurance, futures and options, and government programs. Among these subsidized crop insurance is widely adopted by the farmer. As a result of purchasing crop insurance, a farmer may change production decisions depending on his risk attitudes and the fairness of insurance (Ahsan, Ali, and Kurian). The most studied production decisions include land allocation and variable input use, especially nutrients and pesticides (Babcock and Hennessey; Horowitz and Lichtenberg; Smith and Goodwin). To maintain focus, this paper only considers land allocation as a production decision. Also including variable input use makes the model rather complicated without little gain in terms of conceptual understanding.

Because crop insurance also benefits the external equity investor, he may require crop insurance or specify a certain level of coverage in the contract (Leatham, McCarl, and Richardson). The investor may also want to adjust the contract to induce the farmer's best effort, since crop insurance may change the farmer's production decisions and hence the risks both the farmer and the investor face. To better understand these relationships, we develop a principal-agent model of the contract between the external equity investor and the farmer when the farmer can purchase crop insurance.

Many principal-agent models of sharecropping and crop insurance have been developed, primarily focused on the design of optimal contracts to prevent adverse selection and moral hazard (e.g. Canjels and Volz; Chambers; Nelson and Loehman; Skees and Reed; Ahsan, Ali, and Kurian; Raviv; Allen and Lueck). Principal-agent models have also been used to analyze agricultural financing contracts (e.g., Wang, Leatham, and Chaisantikulawat; Santos). Wang, Leatham, and Chaisantikulawat studied risk sharing and incentives with external equity financing, but did not incorporate risk management tools such as crop insurance or risk averse investors.

This paper first determines an investor's preferences for crop insurance based on the farmer's production decisions and then determines the optimal contract between the investor and the farmer with crop insurance and external financing. Those aims can be done with several assumptions about risk attitudes and fairness of insurance. For production decisions with crop insurance, we assume a risk neutral insurer and a risk averse farmer. For the contract between the investor and the farmer, we assume a risk averse investor and a risk averse farmer with fair and unfair insurance, and use the case of no insurance for comparison.

Farmer Production Decisions with Crop Insurance

Following Ahsan, Ali, and Kurian, we develop a model of a risk averse farmer allocating total acreage M to either a risky crop or a safe (risk-free) crop. Denoting investment in the risky crop as the acreage A, then the investment in the safe crop is $M - A$. Two states of nature exist—a good state with probability $1 - \rho$ and a bad state with probability ρ. The farmer purchases actuarially fair crop insurance that pays the indemnity $aF(A)$ when the bad state occurs, where a is the insurance coverage level and $F(\cdot)$ is the revenue production function for risky crop acreage ($F' > 0$). The farmer pays an insurance premium $a\gamma A$ regardless of the state, where γ is the per acre premium for the risky crop. For the insurance to be fair, the premium $a\gamma A$ must equal the expected indemnity $\rho aF(A)$.

Given these assumptions, farmer income in the good state is $Y_1 = F(A) + r(M - A) - a\gamma A$, where r is the rate of return for the safe asset $(M - A)$, and $Y_2 = aF(A) + r(M - A) - a\gamma A$ in the bad state. Thus random farmer income Y is:

$$Y = \begin{cases} Y_1 = F(A_f) + r(M - A_f) - a_f\gamma A_f & \Pr = 1-\rho \\ Y_2 = a_f F(A_f) + r(M - A_f) - a_f\gamma A_f & \Pr = \rho \end{cases}, \quad (1)$$

where the subscript f denotes the optimal acreage allocation and coverage level the farmer chooses with fair insurance.

For actuarially unfair insurance, the insurer collects more than the fair premium to pay insurance administrative costs and earn a normal rate of return. This additional payment is typically a proportional adjustment c of the fair premium, so that the unfair premium is $(1 + c)\rho aF(A)$. Assuming a competitive market, the insurer's expected profit will equal zero. Given unfair insurance, the risk averse farmer chooses the coverage level a and risky crop acreage A to maximize expected utility $U(\cdot)$ subject to the insurer's zero profit condition. Thus the objective and constraint are

$$\max_{a_u, A_u} \ (1-\rho)U(Y_1) + \rho U(Y_2) \quad (2)$$

$$a_u\gamma A_u - a_u(1+c)\rho F(A_u) = 0, \quad (3)$$

where the subscript u denotes the optimal coverage level and acreage allocation with unfair insurance.

Rearranging the first order condition for the insurance coverage level a_u gives

$$\frac{U'(Y_1)}{U'(Y_2)} = \frac{1-\rho(1+c)}{(1-\rho)(1+c)} = \frac{1-\rho-\rho c}{1-\rho-\rho c+c} < 1. \quad (4)$$

Since income in the good state exceeds income in the bad state ($Y_1 > Y_2$), then the optimal coverage level must be less than one ($a_u < 1$), implying that the farmer does not buy full insurance, but self-insures some of the risk.

Rearranging the first order condition for risky crop acreage A_u gives the relationship

$$(5) \qquad F'(A_u) > \frac{r}{1-\rho-a_u\rho c}.$$

Using equation (5) and results from Ahsan, Ali, and Kurian gives $F'(A_u) > \frac{r}{1-\rho-a_u\rho c}$ $> F'(A_n) > \frac{r}{1-\rho} = F'(A_f) = F'(A_0)$, where A_n, A_f, and A_0 respectively denote optimal risky crop acreage for a risk averse farmer without insurance, a risk averse farmer with fair insurance, and the risk neutral farmer. As a result, optimal risky crop acreage for a risk averse farmer with fair insurance is the same as for a risk neutral farmer, but exceeds optimal risky crop acreage for a risk averse farmer without crop insurance, which must exceed optimal risky crop acreage for a risk averse farmer with unfair insurance: $A_0 = A_f > A_n > A_u$. Let μ and σ^2 respectively denote the mean and variance of revenue from the risky crop. Assuming both are proportional to risky crop acreage, the optimal acreage ordering gives the following ordering for the revenue means and variances: $\mu_0 = \mu_f > \mu_n > \mu_u$ and $\sigma_0^2 > \sigma_n^2 > \sigma_u^2 > \sigma_f^2$, as summarized in Table 1.

Applying standard comparative static methods to equation (5) gives $\frac{\partial F'(A_u)}{\partial a_u} > 0$ and $\frac{\partial F'(A_u)}{\partial c} > 0$, which imply $\frac{\partial A_u}{\partial a_u} < 0$ and $\frac{\partial A_u}{\partial c} < 0$. Thus land allocated to the risky crop decreases with the insurance coverage level and the unfairness of crop insurance. With a convex loading factor instead of linear loading factor, this effect likely is stronger (Chambers and Quiggin).

Equity-Investor's Preferences for the Farmer's Purchase of Crop Insurance

When crop insurance is fair, a risk neutral investor prefers that the farmer purchase crop insurance because the farmer then behaves as a risk neutral farmer and maximizes expected revenue. This is consistent with the farmer's preferences, since with fair crop insurance, the farmer's expected revenue increases as a result of the acreage reallocation and downside risk is eliminated. With unfair crop insurance, a risk neutral investor prefers that the farmer not buy crop insurance, since the associated acreage reallocation causes a decrease in the farmer's expected revenue. However, for a range of premium loads, the farmer prefers to buy crop insurance since he is willing to tradeoff the decrease in downside risk with the decrease in mean revenue. When crop insurance is fair and the investor is risk averse, the investor prefers that the farmer purchase crop insurance because, after the associated acreage allocation, the insurance increases mean revenue and decreases downside risk. When crop insurance is unfair and the investor is risk averse, the investor's preferences for the farmer's purchase of crop insurance are unclear, depending on the investor's trade off between expected revenue and variance relative to the farmer's tradeoff. Table 2 summarizes the investor's preferences for crop insurance.

Principal-Agent Model of an External Equity Investor and a Farmer

We develop a principal-agent model of the contractual relationship between an external equity investor and a farmer. This model extends the work of Wang, Leatham, and

Chaisantikulawat by assuming a risk averse investor and allowing the farmer to purchase crop insurance. We also incorporate the farmer's production decision under crop insurance as presented in the previous section.

An investor and a farmer share the cost M of an investment using external equity and retained earnings. The farmer's share is δ and the investor must invest the remainder $(1 - \delta)$, where $0 < \delta < 1$. The business outcome is stochastic as a result of uncertain production or market price or both. For convenience[1], the output price is normalized to one and only agricultural output q is stochastic. The farmer's effort level (e) is a continuous choice variable for the farmer that affects the distribution of output. For notation, denote the conditional probability density function for output as $f(q \mid e)$. The output distribution when the farmer exerts effort level e_1 first order stochastically dominates the output distribution when the farmer exerts effort level $e_0 < e_1$. The crop output is observable, but not the farmer's effort, which creates a moral hazard problem.

Because effort causes disutility for the farmer, the farmer is willing to tradeoff effort and the associated shift in the output distribution. However, because of the effect of effort on the output distribution, the investor prefers the farmer to exert higher effort, since effort has no direct cost to the investor. To induce the farmer to exert the desired effort, the investor must create a contract that gives the farmer the appropriate incentive. However, the contract can only compensate the farmer based on the observable output, not on the unobservable effort. Denote this compensation as $t(q)$, where q depends on the farmer's effort level e, the crop insurance coverage level $a(\hat{q})$, and stochastic yield $\tilde{\theta}$.

From the investment, the investor and the farmer's payoff are proportional to output q minus the compensation $t(q)$ to the farmer. The investor and the farmer's profit function are

(6) $$\pi_p = (1-\delta)\left(q(e,\hat{\theta},\tilde{\theta}) - t(q)\right)$$

(7) $$\pi_a = \delta\left(q(e,\hat{\theta},\tilde{\theta}) - t(q)\right) + t(q),$$

where the subscripts p and a denote the investor (principal) and the farmer (agent).

Following standard assumptions, we assume farmer's effort cost function $c(e)$ is separable from the utility function, where $c' > 0$ and $c'' > 0$ (Laffont and Martimort). So that the farmer is willing to take the contract, the investor must ensure the farmer's expected utility with the contract equal or exceeds his reservation utility $\overline{U}$, the expected utility from his next best option. This participation or individual rationality constraint (IRC) is

(8) $$\int_q U(\pi_a) f(q \mid e)\, dq - c(e) \geq \overline{U}.$$

[1] We also suppress the subscript in risky crop acreage, A, from now on.

Since farmer effort is unobservable, the investor must also ensure that the contract gives the farmer the incentive to exert the desired effort. This incentive compatibility constraint (ICC) requires that if the farmer accepts the contract, his expected utility when exerting high effort equals or exceeds his expected utility with low effort. Mathematically, this ICC can be expressed as follows:

$$\text{(9)} \qquad \arg\max_{e} \int_{q} U(\pi_a) f(q \mid e) dq - c(e) .$$

As specified, condition (9) cannot be implemented when solving the investor's optimization problem. The First Order Approach (Laffont and Martimort) is a commonly used to replace this global condition with a local condition consisting of the first order condition for problem (9):

$$\text{(10)} \qquad \int_{q} U'(\pi_a) \frac{\partial \pi_a}{\partial e} f_e(q \mid e) dq - c'(e) = 0 .$$

Thus the investor's problem is to find the contractual compensation $t(q)$ and effort level e that maximize his expected utility $V(\cdot)$ of income π_p:

$$\text{(11)} \qquad \max_{t(q),e} \int_{q} V(\pi_p) f(q \mid e) dq ,$$

subject to the individual rationality constraint (8) and the incentive compatibility constraint (10).

To derive an explicit solution, we introduce the Linear-Exponential-Normal (LEN) model of Spremann. We also introduce crop insurance by linking to the previous model and assuming a random yield of $\tilde{\theta} = F(A) + r(M - A)$, where $\tilde{\theta}$ has as normal distribution with mean μ and variance σ^2, $\tilde{\theta} \sim N(\mu, \sigma^2)$ (Weninger and Just). Thus, the outcome with crop insurance is:

$$\text{(12)} \qquad q(e, \hat{\theta}, \tilde{\theta}) = e + \tilde{\theta} + I(\hat{\theta}, \tilde{\theta}) - p(\hat{\theta}) ,$$

where $I(\hat{\theta}, \tilde{\theta})$ is the indemnity ($\max[(\hat{\theta} - \tilde{\theta}), 0]$) and $p(\hat{\theta})$ is the insurance premium. Equation (12) shows the conditional distribution of output given effort. When crop insurance is actuarially fair, the insurance premium equals the expected indemnity, and when it is unfair, the insurance premium exceeds the expected indemnity: $p(\hat{\theta}) \geq E[I(\hat{\theta}, \tilde{\theta})]$.

A farmer compensation scheme is linear in the outcome. The investor pays a fixed payment and a varying payment that is proportional to output: $t(q) = w + bq$. Note that w can be negative, implying that the farmer must make some initial investment or expenditure, but b will be positive, otherwise the farmer will have no incentive to exert any effort. A convex quadratic function is used for the farmer's effort cost function: $c(e) = e^2$, implying increasing marginal disutility for effort.

A constant absolute risk aversion (CARA) utility function is used for both the investor and the farmer. Since yield has a normal distribution, the investor's income also has a normal distribution. In addition, since the compensation function is a linear transformation of yield, the farmer's income also has a normal distribution. As a result, both the investor's and the farmer's expected utility can be expressed in terms of the mean and variance of their respective incomes:

(13) $$\mathrm{E}[U(\pi_p)] = \mathrm{E}[\pi_p] - 0.5\alpha_p \operatorname{var}(\pi_p)$$

(14) $$\mathrm{E}[U(\pi_a)] = \mathrm{E}[\pi_a] - 0.5\alpha_a \operatorname{var}(\pi_a)$$

where α_p and α_a are the coefficients of absolute risk aversion for the investor and farmer.

Optimal Contract for External Equity Financing with Crop Insurance

For the model as specified, farmer profit is:

(15) $$\pi_a = \delta\left[e + \tilde{\theta} + I(\hat{\theta}, \tilde{\theta}) - p(\hat{\theta}) + w + b\left(e + \tilde{\theta} + I(\hat{\theta}, \tilde{\theta}) - p(\hat{\theta})\right)\right] - e^2 .$$

Based on the specified model, the mean and variance of farmer profit is then:

(16) $$E[\pi_a] = [(1-\delta)b + \delta]\mu + \delta e + (1-\delta)(w + be) - e^2$$

(17) $$Var(\pi_a) = [\delta + (1-\delta)b]^2 \sigma^2 ,$$

where $\sigma^2 = Var(\tilde{\theta} + I(\hat{\theta}, \tilde{\theta}))$ represents the truncated variance, since crop insurance removes downside risk, so that profit variance with crop insurance is less than without crop insurance. Given the compensation parameters *w* and *b*, the farmer chooses his effort to maximize his expected utility:

(18) $$\max_e \, [\delta + (1-\delta)b]\mu + \delta e + (1-\delta)(w + be) - e^2 - 0.5\alpha_a [\delta + (1-\delta)b]^2 \sigma^2 .$$

Solving the first order condition for this problem gives the farmer's optimal effort e^*:

(19) $$e^* = 0.5[\delta + (1-\delta)b].$$

Substituting this effort level into individual rationality constraint (8) and solving for *w* gives:

(20) $$w^* = \frac{1}{1-\delta}\left\{\overline{U} - [\delta + (1-\delta)b]\mu - 0.25[\delta + (1-\delta)b]^2 * \left(1 - 2\alpha_a \sigma^2\right)\right\} .$$

The investor's optimal fixed compensation *w* increases in the farmer's reservation utility $\overline{U}$ and decreases in the farmer's expected profit. If the risk aversion parameter, α_a, and variance term, σ^2, are positive and small enough, the fixed compensation decreases with the introduction of crop insurance because it has an effect of decreasing risk, thus making $\left(1 - 2\alpha_a \sigma^2\right)$ increase.

The investor's profit with crop insurance is:

$$(21) \qquad \pi_p = (1-\delta)\left[(1-b)(e+\tilde{\theta}+I(\hat{\theta},\tilde{\theta})-p(\hat{\theta}))-w\right].$$

Based on the specified model, the mean and variance of the investor's profit is:

$$(22) \qquad E(\pi_p) = (1-\delta)[(1-b)(e+\mu)-w]$$

$$(23) \qquad Var(\pi_p) = (1-\delta)^2(1-b)^2\sigma^2$$

Expected profit with and without insurance are equal because the insurance is fair. The variance depends on farmer's risk attitude, the existence of crop insurance, the fairness of crop insurance, and insurance coverage level. Substituting equations (22) and (23) into the investor's objective in equation (11) and simplifying gives:

$$(24) \qquad \underset{b}{Max}\begin{pmatrix} (1-\delta)\left[(1-b)\left(0.5[\delta+(1-\delta)b]+\mu\right)\right] \\ -\left\{\bar{U}-[\delta+(1-\delta)b]\mu-0.25[\delta+(1-\delta)b]^2 * \left(1-2\alpha_a\sigma^2\right)\right\} \\ -0.5\alpha_p(1-\delta)^2(1-b)^2\sigma^2 \end{pmatrix}$$

Solving the first order condition for *b* gives:

$$(25) \qquad b^* = \frac{1}{1-\delta}\left[\frac{\left(1+2\alpha_p\sigma^2\right)}{\left(1+2(\alpha_a+\alpha_p)\sigma^2\right)}-\delta\right].$$

Using this result, several comparative static results can be obtained. The variable compensation rate b^* depends inversely on the farmer's share of investment: $\frac{\partial b^*}{\partial \delta} < 0$. This occurs because the greater the farmer's share of the investment, the greater farmer's incentive to exert effort. The variable compensation rate b^* decreases with the farmer's risk aversion because the farmer needs to bear less risk to motivate high effort: $\frac{\partial b^*}{\partial \alpha_a} < 0$. On the other hand, as the investor's risk aversion increases, the variable compensation rate b^* also increases, $\frac{\partial b^*}{\partial \alpha_p} > 0$, because the investor wants to share more risk with farmer. As the variance of the outcome increases, the variable compensation rate b^* decreases, $\frac{\partial b^*}{\partial \sigma^2} < 0$, because a smaller b^* gives the farmer relatively less risk. Thus overall, crop insurance leads to the increase in variable compensation because it reduces the risk. Because of this effect of crop insurance, the investor must increase the farmer's risk share from the contract to motivate high effort. In effect, crop insurance insulates the farmer from sufficiently powerful incentives to motivate high effort, so the investor compensates by increasing the variable compensation rate to increase the farmer's risk share. Furthermore, we know that the variable compensation rate increases with an increase in the insurance coverage level because $\frac{\partial A}{\partial a} < 0$ and $\frac{\partial \sigma^2}{\partial A} > 0$.

Substituting the optimal b^* into equations (19) and (20) gives the optimal w^* and e^*:

$$(26)\qquad e^* = 0.5\left[\frac{\left(1+2\alpha_p\sigma^2\right)}{\left(1+2(\alpha_a+\alpha_p)\sigma^2\right)}\right]$$

$$(27)\qquad w^* = \frac{1}{(1-\delta)}\left[\bar{U} - \left(\frac{\left(1+2\alpha_p\sigma^2\right)}{\left(1+2(\alpha_a+\alpha_p)\sigma^2\right)}\right)\mu - 0.25\left(\frac{\left(1+2\alpha_p\sigma^2\right)}{\left(1+2(\alpha_a+\alpha_p)\sigma^2\right)}\right)^2\left(1-2\alpha_a\sigma^2\right)\right]$$

Again, several comparative static results can be obtained. The optimal level of effort increases with the investor's risk aversion and decreases with the farmer's risk aversion and the variance of outcome: $\frac{\partial e^*}{\partial \alpha_p} > 0$, $\frac{\partial e^*}{\partial \alpha_a} < 0$, and $\frac{\partial e^*}{\partial \sigma_A^2} < 0$. Because the farmer's compensation is highly dependent on output, the farmer must exert more effort relative to the case without insurance. Also the insurance coverage level increases the optimal level of effort because $\frac{\partial A}{\partial a} < 0$ and $\frac{\partial \sigma^2}{\partial A} > 0$.

The optimal level of the fixed compensation w decreases with the investor's risk aversion $\frac{\partial w^*}{\partial \alpha_p} < 0$. This means that the risk averse investor wants to share more risk with the farmer, and thus decreases the fixed compensation. The optimal level of the fixed compensation increases with the variance of outcome $\frac{\partial w^*}{\partial \sigma^2} > 0$, resulting in the increase with the insurance coverage level. It also increases with the farmer's risk aversion $\frac{\partial w^*}{\partial \alpha_a} > 0$. Thus the investor needs to increase the fixed compensation to induce the participation of the risk averse farmer in the contract. The optimal level of fixed compensation also increases with the farmer's investment share $\frac{\partial w^*}{\partial \delta} > 0$. The farmer with high investment share would be willing to exert effort, thus the investor increases fixed compensation instead of variable compensation. Similarly, the optimal level of fixed compensation increases with the farmer's reservation utility, $\frac{\partial w^*}{\partial \bar{U}} > 0$, and decreases with expected revenue, $\frac{\partial w^*}{\partial \mu} < 0$. Expected revenue is positively correlated with its variance so that the fixed compensation decreases with expected revenue to share more risk.

Crop insurance leads to increase the optimal level of effort through the increase in variable compensation, and decreases the optimal level of fixed compensation. Thus it induces more risk sharing between the investor and the farmer.

Implications

Comparing these results to those of Wang, Leatham, and Chaisantikulawat, we find that the risk neutral or risk averse investor induces more effort, pays more variable compensation, and pays less fixed compensation with crop insurance regardless of fairness of crop insurance. In other wards, crop insurance increases a farmer's optimal effort *e*, and for the optimal contract, crop insurance increases the slope *b* and decreases the intercept *w*. Figures 1 through 5 summarize these results graphically.

In Figure 1, the compensation schedule under crop insurance shows lower fixed payment *w* and higher variable payment rate *b* compared to the case without insurance. This new compensation scheme leads to more risk sharing between the investor and the farmer in order to induce more effort from the farmer. Also these effects become stronger with an increase in the insurance coverage level, as illustrated in figure 2. As expected, a higher coverage level reduces the downside risk further so that the farmer can afford to bear more risk. Thus a higher coverage level leads to a higher variable compensation *b* and effort level *e*, and a lower fixed compensation *w* than with a lower coverage level. Figure 3 shows how the fairness of crop insurance also affects the optimal compensation scheme. Fair insurance decrease more variance than unfair insurance, which gives afford for the farmer to bear more risk. So the contract with more variable compensation and effort, and less fixed compensation is needed.

As the investor's risk aversion increases, the variable compensation *b* and effort level also increase *e* and the fixed compensation *w* decreases because the investor would prefer to share more risk with the farmer, as shown in figure 4. On the other hand, as the risk aversion of farmer increases, opposite results are obtained as shown in figure 5, because the farmer would not accept the contract if the variable compensation is too high.

Conclusion

This paper determines the investor's preferences for crop insurance according to risk attitude and the fairness of the crop insurance. Also, for any given crop insurance, we determine the optimal contract design that induces the best effort from the farmer using a variable compensation rate and a fixed compensation rate.

A risk averse farmer with fair crop insurance behaves like a risk neutral farmer. He allocates more to the risky crop, thus resulting in higher expected revenue and a lower variance, as long as the crop insurance is actuarially fair. So both a risk neutral investor and a risk averse investor prefer a farmer with fair crop insurance. If the insurance is not fair, the risk averse farmer reduces the risky crop acreage compared to the case without insurance. Thus, even though crop insurance decreases the variance of revenue, expected revenue also decreases. Therefore, a risk neutral investor does not like unfair crop insurance, but a risk averse investor must tradeoff between decreased expected revenue and decreased variance. The risk averse investor may prefer unfair crop insurance as long as the benefit from reducing risk is greater than the cost of reducing expected revenue. Given crop insurance, the investor will adjust the compensation scheme to induce the best effort from the farmer. The results show that the investor's optimal contract will use a larger variable compensation rate than without insurance. The variable compensation rate also increases with the coverage level. The optimal contract with fair insurance uses a larger variable compensation rate than unfair insurance. The risk averse investor prefers that the optimal contract depend more on variable compensation than the risk neutral investor. The risk averse farmer is given a larger variable compensation rate than the risk neutral farmer.

Optimal contract requires the farmer to bear more risk so that the farmer has the appropriate incentives to work hard. Thus by making the compensation scheme depend more on variable compensation with crop insurance, the investor may induce more effort from the farmer and share more risk with the farmer. Thus crop insurance may reduce the moral hazard problem caused by asymmetric information.

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Table 1. The results of production decision.*

	Risk Neutral Farmer	Risk Averse Farmer		
	No Insurance	No Insurance	Fair Insurance	Unfair Insurance
Risky Crop Acreage (A)	1	2	1	3
Expected Revenue (μ_A)	1	2	1	3
Revenue Variance (σ_A^2)	1	2	4	3

* Numbers represent farmer rankings from highest (1) to lowest (4).

Smallest number denotes the highest risky crop acreage, expected revenue, and revenue variance in each row. The larger the number, the smaller the magnitude of them.

Table 2. The investor's preference for farmer's purchasing crop insurance.

	Fair Insurance	Unfair Insurance
Risk Neutral Investor	Prefer	Not Prefer
Risk Averse Investor	Prefer	Uncertain

Figure 1. The effect of crop insurance on optimal compensation scheme

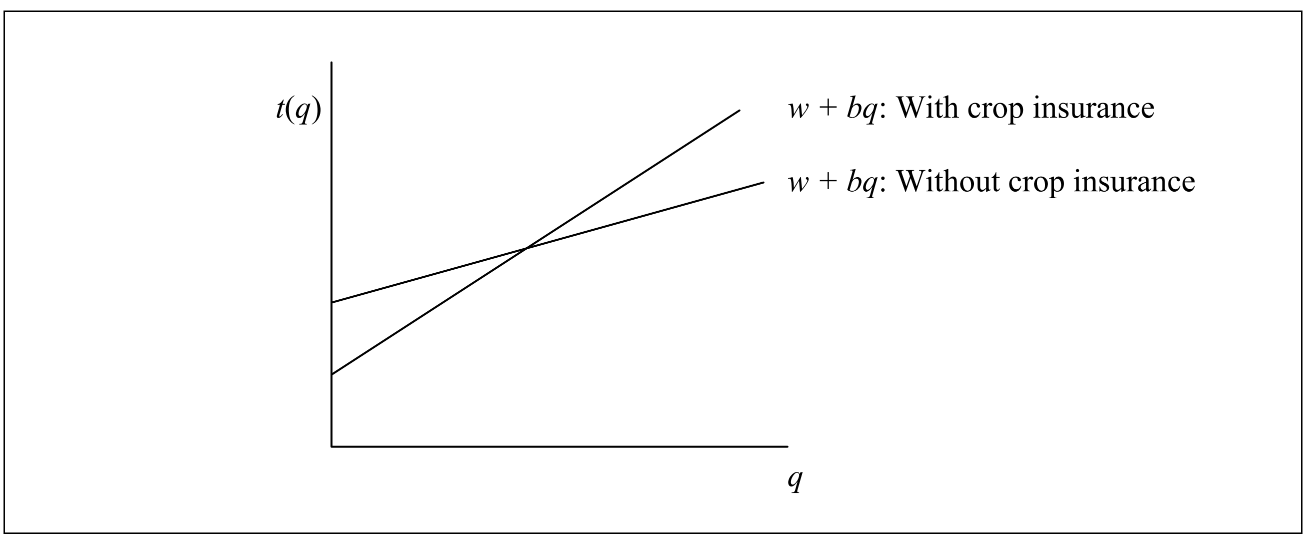


Figure 2. The effect of insurance coverage level on optimal compensation scheme

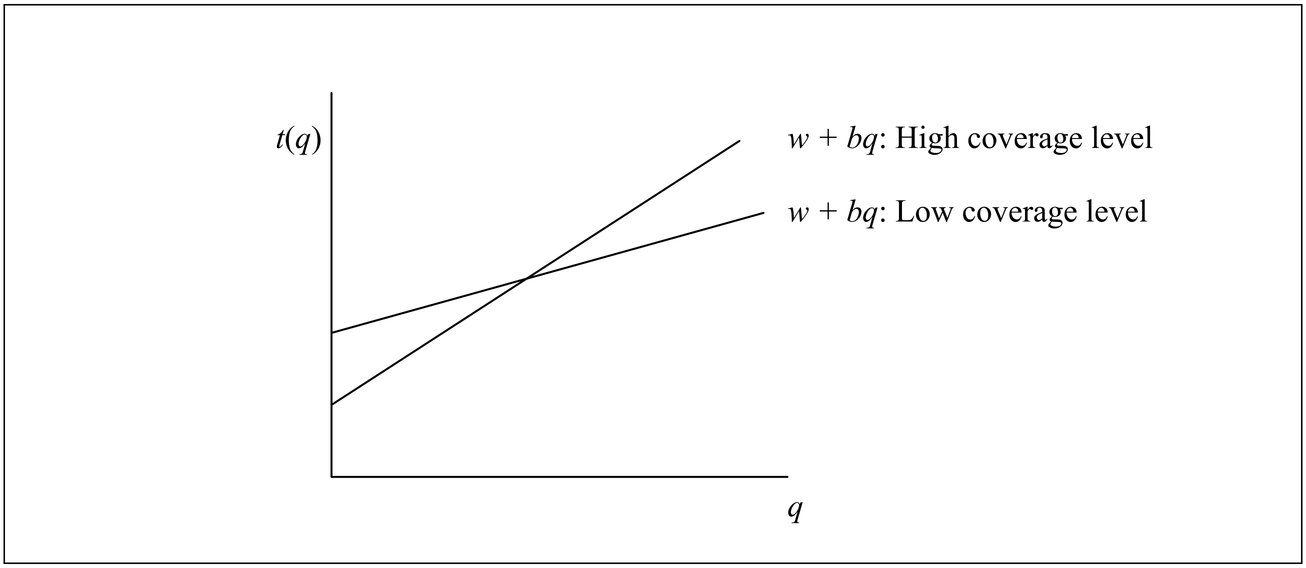


Figure 3. The effect of fairness of insurance on optimal compensation scheme

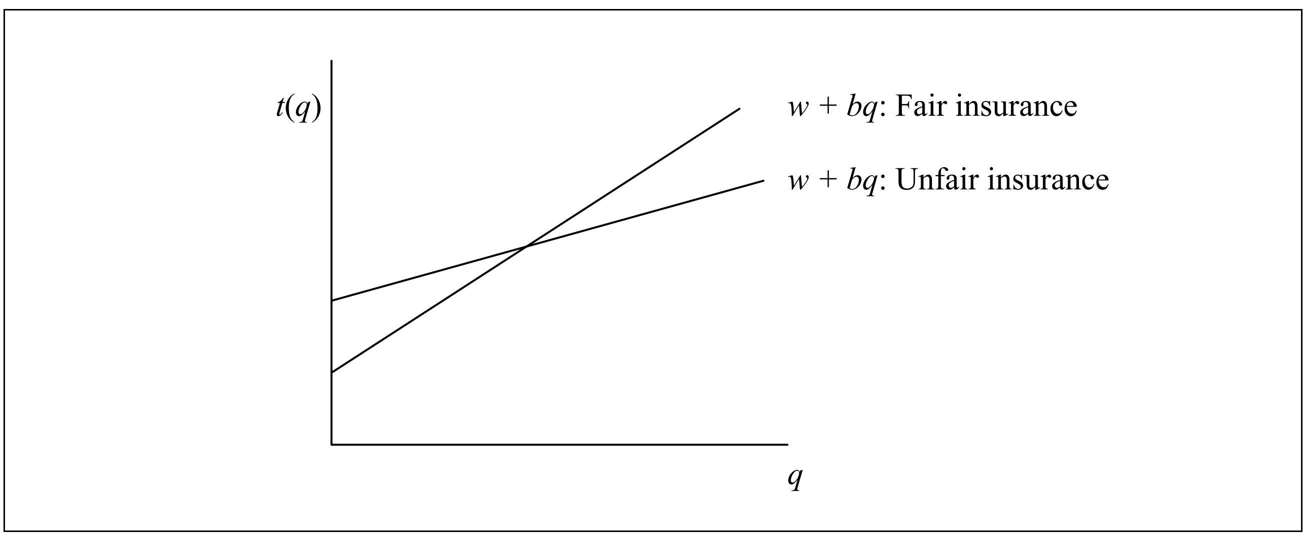


Figure 4. The effect of investor’s risk aversion on optimal compensation scheme

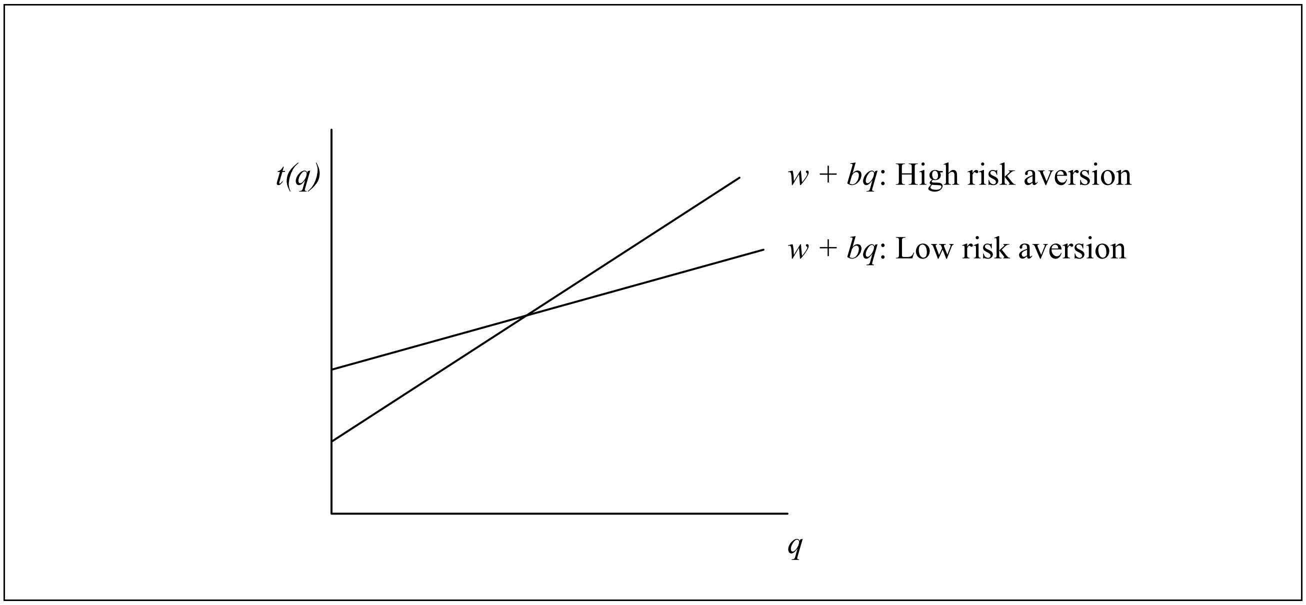
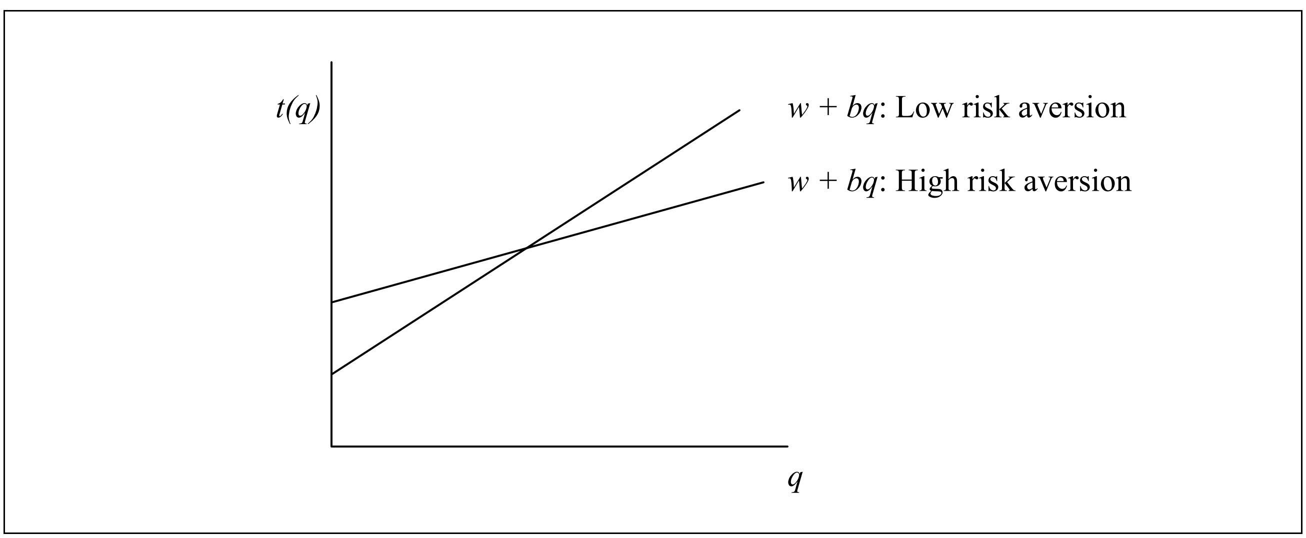


Figure 5. The effect of farmer’s risk aversion on optimal compensation scheme



Input Inefficiency in Commercial Banks:

A Normalized Quadratic Input Distance Approach

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Abstract:

A normalized quadratic input distance function is proposed with which to estimate technical efficiency on commercial banks regulated by the Federal Reserve System. The study period covers 1990 to 2000 using individual bank information from the Call and Banking Holding Company Database. A stochastic frontier model is specified to estimate the input normalized distance function and obtain measures of technical efficiency.

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Input Inefficiency in Commercial Banks:
A Normalized Quadratic Input Distance Approach

Introduction

In this paper we explore technical efficiency of commercial banks over the period 1990 to 2000 using an input distance function approach. The input distance function approach is of interest because it is a valid representation of multiple output technologies and directly measures technical efficiency in producing a given set of outputs. The analysis covers the sample period from 1990 to 2000 using Call and Banking Holding Company Database information for individual commercial banks. In the analysis, we implement a normalized quadratic distance function that characterizes multiple input and output production processes estimated with Bayesian econometrics. The Bayesian method provides a systematic approach for more efficient estimation by imposing parameter and economic restrictions, which are inherent in duality models of firm behavior.

Kaparakis, Miller, and Noulas (1994) provided a review of methodologies and conclusions for eight studies on bank frontier analysis. Past studies have taken non-parametric and parametric estimation approaches, including mathematical programming, stochastic frontier analysis, and simultaneous equation estimation. In addition, studies have used various functional forms such as the translog cost function (Ferrier and Lovell, 1990), profit function (Berger, et al. 1993), and output distance function (English, et al., 1993). The consensus of these studies is that significant inefficiencies exist and were generally declining over time (possibly due to deregulation), banks exhibit better allocative relative to technical inefficiency, and that external factors explains some of the observed inefficiencies. More recently, Berger and Mester (1999) found that cost productivity decreased while profit productivity increased from 1991-1997, particularly for banks involved in mergers. Wheelock and Wilson (2001) examined measures of scale and product mix economies with nonparametric estimation found that banks experience increasing returns to scale up to approximately $500 million dollars in assets. Reported efficiencies in past studies vary over a wide range and comparisons are difficult due to differences in maintained hypotheses, sample, and functional form.

Our methodological focus is on the production side where we specify a form of the normalized quadratic function exhibiting properties consistent with an input distance function. No study to date has explored technical efficiency in banking using input distance function approach. Furthermore, research on normalized quadratic distance functions is limited. On the consumer demand side, Holt and Bishop (2002) recently specified a normalized quadratic distance function and used it to estimate inverse demand relationships for fish. Also, the normalized quadratic input distance function is specified to accommodate both single and multiple output production processes and allows direct testing or imposition of input and output curvature conditions. Even for the case of a single input where the properties of the consumer and input distance function are equivalent (Cornes 1992), the functional specification is different.

To estimate measures of technical efficiency, we exploit the stochastic frontier approach (Stevenson 1980; Greene 1980, 1990; Battese and Coelli 1988). This framework coupled with the normalized quadratic function is sufficiently flexible to impose economic restrictions on both inputs and outputs with Bayesian estimation. We implement a parametric estimator that uses a maximum likelihood function to construct a Bayesian Markov chain Monte Carlo model with economic restrictions imposed following Geweke (1986). This research compliments recent studies by Atkinson and Primont (2002) and Atkinson, Färe, and Primont (2003), who estimated complete systems of inverse demand relationships jointly with the distance function using a GMM estimator. The input distance function is applied to several years during the period 1990 to 2000 to explore changes in technical efficiency that may have occurred over time.

Input Distance Function and Technical Efficiency

Input Distance Function

The direct input distance function is defined by

$$D(\mathbf{x},\mathbf{y}) = \sup_{\delta}\left\{\delta > 0 \mid (\mathbf{x}/\delta) \in S(\mathbf{y}), \forall y \in \mathbf{R}_+^M\right\} \tag{1}$$

where $\delta \geq 1$. In (1), $\mathbf{y}$ is a (m× 1) vector of outputs, $\mathbf{x} = (x_1,\ldots,x_k)'$ is a ($n \times 1$) vector of inputs and $S(\mathbf{y})$ is the set of all input vectors $\mathbf{x} \in \mathbf{R}_+^n$ that can produce the output vector $\mathbf{y} \in \mathbf{R}_+^m$. The underlying behavioral assumption is that the distance function represents a rescaling of all the input levels consistent with a target output level. Intuitively, δ is the maximum value by which one could divide $\mathbf{x}$ and still produce $\mathbf{y}$. The value δ places $\mathbf{x}/\delta$ on the boundary of $S(\mathbf{y})$ and on the ray through $\mathbf{x}$. For example, in Figure 1, the distance function value is $D(x,y)$=OB/OA; the value required to scale the vector x^1 back to x^* on the boundary of $S(\mathbf{y})$. In other words, the input distance function measures the extent to which the firm is input efficient in producing a fixed set of output. Investigating the distance function is interesting because it is a dual representation of the cost function and both are valid representations of multiple output technologies.

The standard properties of a distance function are that it is homogenous of degree one, nondecreasing, and concave in input quantities $\mathbf{x}$, as well as nonincreasing and quasi-concave in outputs $\mathbf{y}$ (Shephard 1970; Färe and Primont 1995). From (1) inverse factor demand equations may be obtained by applying Gorman's Lemma

$$\frac{\partial D(\mathbf{x},\mathbf{y})}{\partial \mathbf{x}} = \mathbf{p}^*(\mathbf{x},\mathbf{y}) \tag{2}$$

where $\mathbf{p}^* = (p_1,\ldots,p_n)'$ is a ($n \times 1$) vector of cost normalized input prices or $p_i^* = p_i / \sum_{j=1}^n p_j x_j$. The Hessian matrix is given by the second order derivatives of the distance function (Antonelli matrix)

$$A = \begin{bmatrix} \dfrac{\partial^2 D(\mathbf{x},\mathbf{y})}{\partial \mathbf{x}\partial \mathbf{x}'} & \dfrac{\partial^2 D(\mathbf{x},\mathbf{y})}{\partial \mathbf{x}\partial \mathbf{y}'} \\ \dfrac{\partial^2 D(\mathbf{x},\mathbf{y})}{\partial \mathbf{y}\partial \mathbf{x}'} & \dfrac{\partial^2 D(\mathbf{x},\mathbf{y})}{\partial \mathbf{y}\partial \mathbf{y}'} \end{bmatrix} \tag{3}$$

Imposing monotonicity constraints require that $\partial D(\mathbf{x},\mathbf{y})/\partial \mathbf{x} \geq \mathbf{0}$ and $\partial D(\mathbf{x},\mathbf{y})/\partial \mathbf{y} \leq \mathbf{0}$, while curvature constraints are based on the eigenvalues of the Antonelli matrix in (3).

Technical Efficiency

The input distance function has been exploited as a measure of technical efficiency (Farrell 1957; Debreu 1951). Inefficiencies arise if firms do not use cost minimizing amounts of input for several reasons, including regulated production, production quotas, or shortages (Atkinson and Primont 2002; Atkinson, Färe, and Primont 2003). The input-oriented measures of technical efficiency are given by

(4) $$TE = 1/D = \inf_{\delta} \{\delta : \delta x \in S(\mathbf{y})\}$$

where *TE* lies between zero and one. This efficiency measure can be equivalently specified as

(5) $$\ln D + \ln TE = \ln D - u = 0$$

where the term $u = -\ln TE$ can be expressed as $TE = \exp(-u)$. Hence, *u* is nonnegative being bounded below by zero and unbounded from above.

Normalized Quadratic Distance Function

To complete the empirical model specification, we specify a normalized quadratic distance function. The normalized quadratic allows explicit investigation of the interactions between inputs and outputs and allows imposition of curvature conditions. The importance of curvature properties was emphasized by Berger, Hancock, and Humphery (1993). Featherstone and Moss (1994) used a normalized quadratic cost function with curvature properties to measure economies of scale and scope in agricultural banking, finding contrasting results in measures of scope and scale with or without curvature restrictions. The proposed normalized quadratic distance function is given by

(6)

$$D(\mathbf{x}, y) = b_0 + \sum_{i=1}^{n} b_i x_i + \sum_{i=n+1}^{n+m} b_i y_i + \frac{1}{2}\left(\left(\sum_{k=1}^{n} \alpha_k x_k\right)^{-1} \sum_{i=1}^{n}\sum_{j=1}^{n} b_{ij} x_i x_j + \sum_{i=n+1}^{n+m}\sum_{j=n+1}^{n+m} b_{ij} y_i y_j\right) + \sum_{i=1}^{n}\sum_{j=n+1}^{n+m} b_{ij} x_i y_j$$

with *n* inputs and *m* outputs. The b_i's and b_{ij}'s are parameters to be estimated, while the α_i are predetermined positive constants that dictate the form of normalization. Symmetry is imposed by restricting $b_{ij} = b_{ji}$. The normalized quadratic distance function in (6) is semiflexible at a reference vector x^* (Diewert and Wales 1988).

Homogeneity of degree zero in inputs in the input demand equations implies that $\sum_{j=1}^{n} b_{ij} = 0$, while the normalization restriction requires that $\sum_{k=1}^{n} \alpha_k x_k = 1$ at a reference vector. Normalizing quantities by their mean values yields unit means, or $x^* = (1,...,1)' = l_n$, which can be used as a reference bundle. At a reference vector x^*, the demand restrictions become

(7) $$\sum_{k=1}^{n} \alpha_k x_k^* = \sum_{k=1}^{n} \alpha_k = 1,\ \alpha_k \geq 0, \forall k \text{, and } \sum_{j=1}^{n} x_j^* b_{ij} = \sum_{j=1}^{n} b_{ij} = 0$$

Stochastic Input-Normalized Distance System

Given the distance function is homogeneous of degree one quantities, then it is possible to normalize by some λ (e.g., an input or output or convex combinations),

(8) $$\frac{1}{\lambda}D(\mathbf{x},\mathbf{y}) = D^*\left(\frac{\mathbf{x}}{\lambda},\mathbf{y}\right) \Leftrightarrow \ln D(\mathbf{x},\mathbf{y}) - \ln\lambda = \ln D^*\left(\frac{\mathbf{x}}{\lambda},\mathbf{y}\right)$$

From (5) the relationship can be rewritten as

(9) $$\ln\lambda = -\ln D^*\left(\frac{\mathbf{x}}{\lambda},\mathbf{y}\right) + u$$

In empirical applications, the term $u = -\ln TE$ has been exploited to form an estimable equation of the distance function itself that provides a direct measure of input inefficiency (Stevenson 1980; Greene 1980; Battese and Coelli 1988; Morrison Paul, Johnston, and Frengley 2000; Brümmer, Glauben, and Thussen 2002).

To define a distance function normalized by the *kth* input let $x_s^* = x_s / x_k \ \forall s = 1,\ldots,n$. Define the predetermined constants as $\alpha = (0,\ldots,0,\alpha_k,0\ldots,0) \ni \alpha_k = 1$, then $\sum_{s=1}^{n} \alpha_s x_s^* = 1$. Using the homogeneity property of the distance function, it can be written as

(10)

$$D^*(\mathbf{x},y) = \frac{D(\mathbf{x}/x_k, y)}{x_k} = b_0^* + \sum_{i=1}^{n-1} b_i^* x_i^* + \sum_{i=n+1}^{n+m} b_i y_i + \frac{1}{2}\left(\sum_{i=1}^{n-1}\sum_{j=1}^{n-1} b_{ij}^* x_i^* x_j^* + \sum_{i=n+1}^{n+m}\sum_{j=n+1}^{n+m} b_{ij} y_i y_j\right) + \sum_{i=1}^{n-1}\sum_{j=n+1}^{n+m} b_{ij} x_i^* y_j$$

Hence, the distance function in (10) is a special case of that in (6). From (9) the *kth* input-normalized distance function can be represented by

(11)

$$\ln x_k = -\ln\left(b_0^* + \sum_{i=1}^{n-1} b_i^* x_i^* + \sum_{i=n+1}^{n+m} b_i y_i + \frac{1}{2}\left(\sum_{i=1}^{n-1}\sum_{j=1}^{n-1} b_{ij}^* x_i^* x_j^* + \sum_{i=n+1}^{n+m}\sum_{j=n+1}^{n+m} b_{ij} y_i y_j\right) + \sum_{i=1}^{n-1}\sum_{j=n+1}^{n+m} b_{ij} x_i^* y_j\right) + u + \varepsilon_0$$

where ε_0 is assumed to be an identically distributed stochastic error term and independent of *u*. Estimation issues concerning (11) are complicated by that fact that *u* is unobserved, but have been addressed in several ways in the stochastic frontier production literature, which we discuss in more detail below.

Econometric Estimation

Following Greene (1980, 1990) the likelihood for the composite error term v is specified as a GAMMA distribution with parameters $\theta > 2$ and $\lambda = 1$, which yields the exponential distribution. For $\theta > 2$ the maximum likelihood estimation of the parameters is a regular case.

The log-likelihood function for (11) becomes

$$(13) \qquad \ln L(\boldsymbol{\beta},\theta,\sigma \mid \mathbf{Y},\mathbf{X}) = \sum\nolimits_{t=1}^{T}\left\{\ln\theta + \left(\theta\sigma\right)^2/2 + \theta\varepsilon_i + \ln\Phi\left[\left(-\varepsilon_i - \theta\sigma^2\right)/\sigma\right]\right\}$$

where σ is the variance of the normal distribution. Under a general set of regularity conditions the maximum likelihood estimates are asymptotically normally distributed and asymptotically efficient.

Markov Chain Monte Carlo

To specify a posterior pdf for either (12) or (13), we assume prior information on the $(\beta',\varphi)'$ with prior pdf $\pi(\theta,\varphi) = \pi(\beta)\pi(\varphi)$. Here, φ represents parameters σ and $\theta > 2$ in (13). The β parameters are assumed to have a noninformative prior (i.e., $\beta \propto$ constant) for either model. For the truncated normal distribution μ is assumed to have uniform distribution bounded below by zero. The inverted gamma is used for a prior on σ, while θ is assumed to have a uniform distribution bounded below by two. These priors have been used in numerous Bayesian studies (e.g., Zellner, Bauwnes, and Van Dijk 1988). The posterior pdf is then as

$$p(\boldsymbol{\beta},\varphi) = L(\boldsymbol{\beta},\sigma,\mu,\sigma_u \mid \mathbf{Y},\mathbf{X})\pi(\beta)\pi(\varphi)$$

Techniques of Markov chain Monte Carlo (MCMC) simulation estimation using the Metropolis-Hastings algorithm are applied to Bayesian estimation (Mittelhammer, Judge, and Miller 2000; Chib and Greenberg).

Empirical Methodology and Data

To estimate a measure of technical inefficiency a theoretically consistent model must be specified. There are two common approaches to modeling banks, the production and intermediation approach. The production approach measures bank production in terms of the numbers of loans and deposit accounts serviced and includes operating costs. The intermediation approach measures outputs in terms of the dollar amounts of loans and deposits and includes operation costs and interest expense. We choose to follow the intermediation approach as have Berger et al (1987), Ferrier and Lovell (1990), Kaparakis, Miller, and Noulas (1994), and Wheelock and Wilson (2001) among others.

The data are from the 1990, 1994 and 2000 Call Report information for commercial banks. Following Kaparakis, Miller, and Noulas (1994) and Wheelock and Wilson (2001) the model includes four outputs, four variable inputs, and one quasi-fixed input. Outputs include loans to individuals (y_1), real estate loans (y_2), commercial and industrial loans (y_3), and federal funds, securities purchased under agreements to resell (y_4). Inputs include interest-bearing deposits except certificates of deposits greater than \$100,000 (x_1), purchased funds (certificates of deposits greater than \$100,000, federal funds purchased, and securities sold plus demand notes) and other borrowed money (x_2), number of employees (x_3), and book value of premises and fixed assets (x_4). The quasi-fixed asset is noninterest-bearing bonds. Kaparakis, Miller, and Noulas (1994) suggest that banks cannot attract more noninterest-bearing deposits by offering interest and they should be regarded as exogenous. The data used in the empirical model are based on average quarterly values across a given year.

Rather than compute input prices, we choose to estimate only the distance function itself in (11) without the system of inverse demand relationships defined by (2). Typically, inverse demand relationships are included to increase econometric efficiency, obtain measures of price flexibilities, or obtain dual cost measures. Our justification is that for large sample sizes the efficiency gains from including the inverse demand system will likely not compensate for the added numerical complexities and computations, and because our interest is technical efficiency that is completely characterized by (11). Moreover, including calculated input prices may introduce measurement error or results in prices with little price variation that can compromise empirical duality properties (Lusk, Featherstone, Marsh, and Abdulkadri).

To arrive at the final data sets for estimation, several data management steps were taken. First, we excluded banks that reported negative inputs or outputs (which only influenced x_1). This yielded 12,395 observations in 1990, 10,765 observations in 1994, and 8,517 observations in 2000. Then to account for extreme outliers, we excluded banks that 6 or more standard deviations away from the mean of the input and output values. In 1990 there were 12,218 remaining observations, in 1994 there were 10,620 remaining observations, and in 2000 there were 8,409 remaining observations. The number of employees (x_3) was used to normalize the other inputs because it had a few reported zero values (e.g., in 2000 there were only eleven zero values). The zero values were assigned the minimum value of the remaining observations in x_3.

Econometric models of (11) were estimated for each year using the Bayesian estimator based on alternative cross-sections of the data. Models were estimated on the entire data set, for banks with total assets less than $50 million, and banks with assets greater than $50 million. Partitioning data in this manner are consistent with previous studies (e.g., Kaparakis, Miller, and Noulas 1994) and allows comparison and testing of results between smaller and larger banks (as well as across the entire sample). A histogram of the number of banks across total assets is presented in Figure 2, showing a steady decrease (increase) in the number of banks with total assets under (over) $50 million.

To complete the MCMC simulation of the Bayesian estimator, a burn-in period of 30,000 iterations was used. These iterations were then discarded and 70,000 additional iterations were simulated to yield the final empirical distribution. Additional details of the data and the MCMC analysis are available from the authors upon request. Curvature conditions are imposed using Cholesky decomposition (Lau 1970).

Results and Discussion

Empirical results are presented in Table 1 for 1990, 1994, and 2000. For convenience we summarize these results with the median, mean, and standard deviation of technical efficiency in Table 1 for the Bayesian exponential model.

In general, the preliminary technical efficiency estimates are consistent with those obtained in Berger et al. (1993) and English, et al. (1993). English et al. (1993) report a mean output technical efficiency of 0.754 with standard deviation of 0.145 for small commercial banks in 1982. Focusing on the results from the exponential model over the entire sample, input efficiency has increased over the sample period and were higher for larger banks. In 1990 and 1994, the median efficiency values were nearly identical yielding 0.732 and 0.730, respectively. In 2000, the median efficiency level over the entire sample increased to 0.754. For smaller banks (total assets less than $50 million) the median technical efficiency measure incremented from 0.696 in 1990, to 0.704 in 1994, and to 0.715 in 2000. For larger banks (total assets greater than $50 million) the median technical efficiency measure increased from 0.75 in 1990 and leveled off to 0.80 in 1994 and 2000. Comparing across bank sizes, larger banks were more 7%, 14%, and 11% more efficient than smaller banks in 1990, 1994, and 2000 respectively. Note that, when comparing the mean technical efficiency measures, the differences would reduce to 0%, 6%, and 4% in 1990, 1994, and 2000 respectively. In all, these results are consistent with the interpretation that bank efficiency has been increasing over time (Kaparakis, Miller, and Noulas 1994) and that the larger banks exhibit higher technical efficiency levels (Berger, et al. 1993).

Results were also obtained by estimating (11) without curvature restrictions in 2000, providing mixed results. For smaller banks, relaxing curvature conditions increased technical efficiency. For larger banks, relaxing curvature conditions decreased technical efficiency. Across the entire sample, the technical efficiency measures were nearly identical. Although the results are mixed, it is apparent that technical efficiency results are sensitive to curvature restrictions. However, the direction of this effect was not consistent between smaller and larger banks.

Conclusions

In this paper a normalized quadratic input distance function is proposed with which to estimate technical efficiency on commercial banks regulated by the Federal Reserve System. The study period covers 1990 to 2000 using individual bank information from the Call and Banking Holding Company Database. A Bayesian variation of a stochastic frontier model is used to estimate the input normalized distance function and obtain measures of technical efficiency. Preliminary findings based on 1990, 1994, and 2000 data are consistent with previous findings in that technical inefficiency appears to be decreasing over time and that larger banks are more efficient. We recognize limitations of the research presented in this paper. Perhaps most importantly, technical efficiency estimates were based only on selected years. Our intention is to revisit and extend the empirical analysis by using a panel data set from 1990 to 2000.

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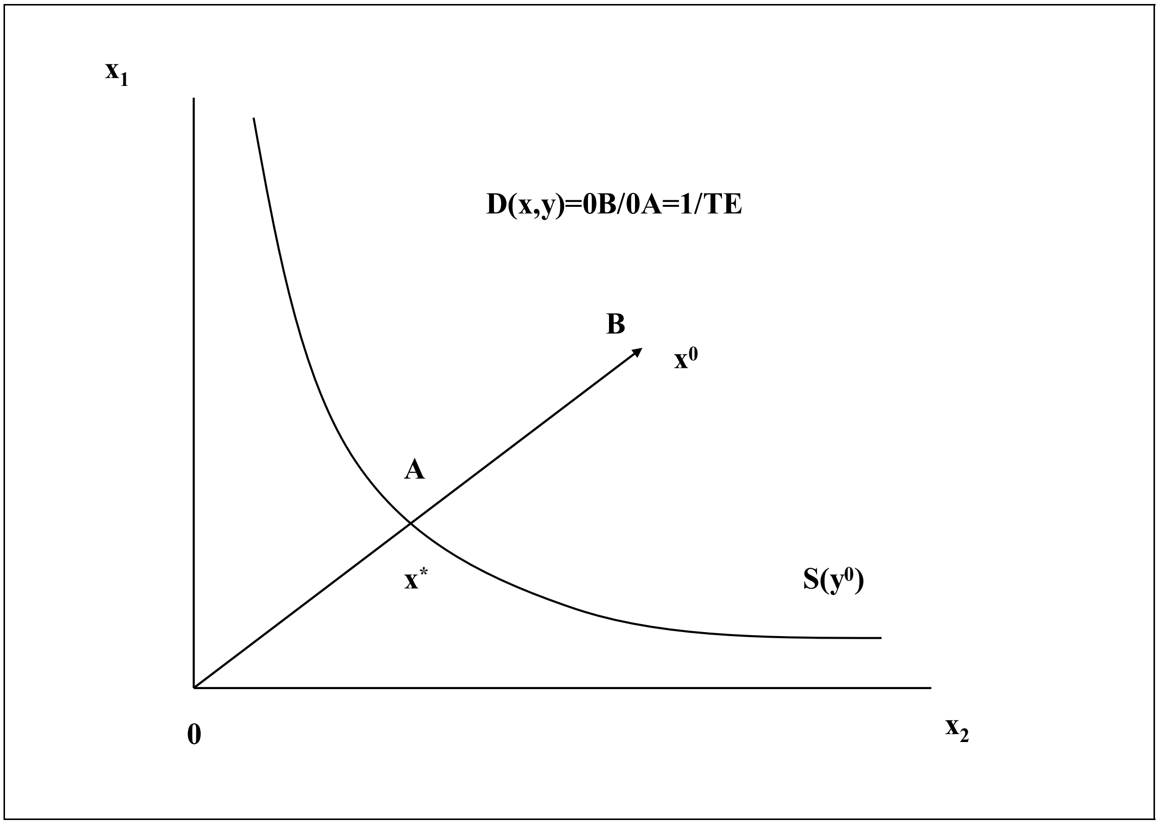

Figure 1. The Distance Function and Input Efficiency.

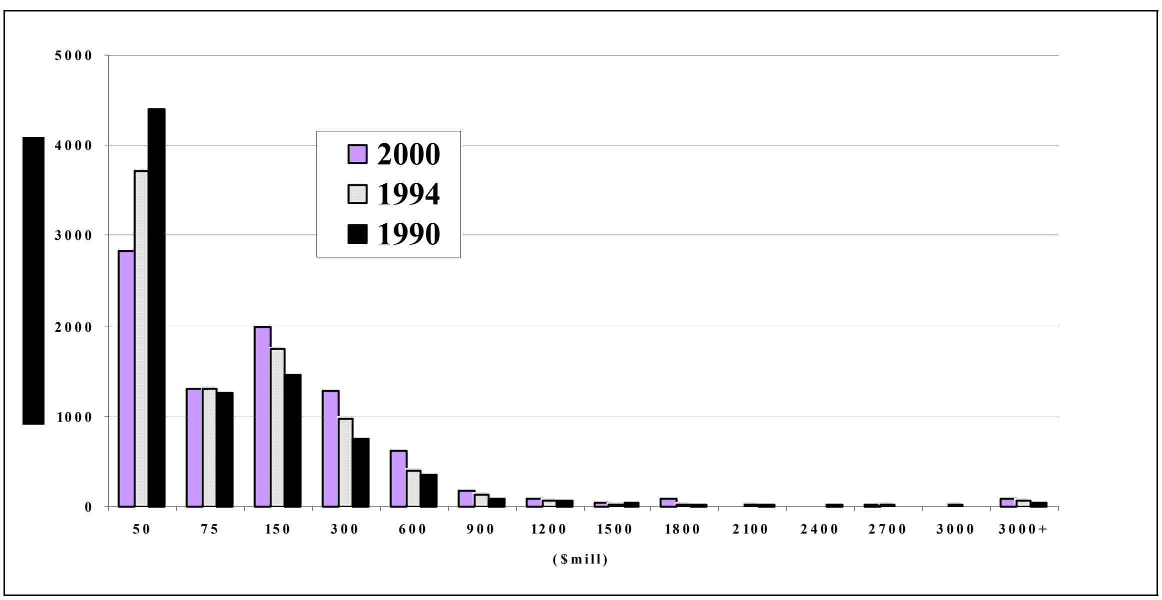

Figure 2. Number of Commercial Banks by Total Assets.

Table 1. Technical Efficiency Measures from Stochastic Exponential Model

Year	Median	Mean	Standard Deviation	
	Small Commercial Banks			
1990	0.696	0.696	0.113	
1994	0.704	0.709	0.112	
2000	0.715	0.716	0.100	w/curvature
	0.738	0.739	0.096	wo/curvature
	Large Commercial Banks			
	Median	Mean	Standard Deviation	
1990	0.754	0.705	0.141	
1994	0.800	0.750	0.154	
2000	0.801	0.749	0.166	w/curvature
	0.768	0.721	0.164	wo/curvature
	All Commercial Banks			
	Median	Mean	Standard Deviation	
1990	0.732	0.683	0.155	
1994	0.730	0.685	0.145	
2000	0.754	0.703	0.161	w/curvature
	0.755	0.704	0.162	wo/curvature

Analysis of Borrower and Lender Use of Interest Assistance on FSA Guaranteed Farm Loans

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This paper was presented at the annual meeting of the Multistate Research Coordinating Committee/Information Exchange Group, NCT194 Agricultural Finance Markets in Transition. Federal Reserve Bank of Kansas City, Kansas City, Missouri, October 6-7, 2003.

Analysis of Borrower and Lender Use of Interest Assistance on FSA Guaranteed Farm Loans

Section 5313 of The Farm Security and Rural Investment Act of 2002 made permanent the interest assistance (IA) program for the Farm Service Agency's (FSA) guaranteed loans. The Act authorizes the Secretary of Agriculture to fund this program up to $750 million in lending per year, a considerable increase from amounts authorized in previous years. Moreover, the Act states that not less than 15 percent of annual funding shall be reserved for beginning farmers and ranchers. Even though the program has been in existence for more than 15 years, little is known about its impact and utilization.

This research provides a basic descriptive analysis of past IA use. In particular, borrower data for Federal fiscal years 1985 through 2002 are examined in several dimensions. First, the geographical distribution of IA payments is documented. It is known that the distribution throughout the 1990s of IA use was not uniform across the United States. The analysis updates this distribution. Moreover, it is not known what types of borrowers use the IA program. The analysis investigates how the use of IA is distributed over beginning farmers, socially disadvantaged farmers (SDA) and borrowers who are not in either of the two prior groups. These outcome data are examined across the categories of beginning, SDA, and other farmers. Use of interest assistance by lender type are also explored with lender categorization being commercial bank, Farm Credit System, savings and loan, Credit Union, mortgage company, and other lenders.

Another aspect of the analysis examines interest rate differentials between loans to borrowers not receiving interest assistance and those that do. According to the FSA Handbook, *Guaranteed Loan Making and Servicing*, interest rates charged on guaranteed loans cannot "…exceed the rate the lender charges its average agricultural loan customer." This applies to loans receiving interest assistance as well as loans not receiving interest assistance. The research investigates if the average rate charged to IA borrowers before the subtraction of IA differs from the rate charged to those guaranteed borrowers not receiving IA.

Finally, analysis compares the success rates of IA users versus non-users where success is defined as completing the loan without having a loss claim paid. This finding has significant policy implications because a primary objective of the program is to assist borrowers in avoiding default.

History of Interest Assistance Program

Interest rate assistance was originally enacted with the Food Security Act of 1985 (P.L. 99-198). Section 1716 authorized an interest rate reduction program for 3 years, ending on September 30, 1988 to be administered by the U.S. Department of Agriculture's Farmers Home Administration (FmHA).[2] This program was originally established to make payments to "legally regulated" lending institutions that reduce interest rates of borrowers of loans guaranteed by the Secretary of Agriculture. Stipulations were that (1) borrowers that participate in this program must meet the established eligibility requirements which include that they operate a "not larger than family size farm" after the loan is closed and they demonstrate an inability to obtain credit from other lenders at reasonable rates and terms; (2) a borrower must not have been able to make payments on the loan in a timely manner without the benefit of the interest rate reduction; (3) the borrower must have a projected cash flow after the interest rate reduction of at least 100%; and (4) the lender must agree to reduce the interest rate by a minimum amount established by the

[2] FmHA's farm loan programs were moved to the newly formed FSA in 1994 and FmHA ceased to exist.

Secretary. In return, the Secretary would make payments to the lender equal to the amount of the interest reduction up to 2 percentage points. Thus, the program was commonly referred to as the buydown program. The terms were to be not more than 3 years or for the term of the loans, whichever is less [Ref: House Conference Report 99-447; Senate Report 99-145].

In the original House and Senate reports, there is little explanation as to the thoughts of policymakers in initiating this legislation. But, during this time period there were two issues affecting credit policy that may have influenced the passage of this legislation. One was the desire to increase the use of guaranteed credit among lenders and reduce direct lending by the U.S. Department of Agriculture. Secondly, there were concerns about the impacts relatively high interest rates were having on farmers' financial conditions. The drafters of this legislation may have envisioned the buydown program as an inducement to lenders to utilize the guaranteed loan program to refinance farmer loans at lower interest rates and longer terms, thereby providing borrowers some relief from their relatively high debt service obligations.

The buydown program was addressed again in the Agricultural Credit Act of 1987 [P.L. 100-233]. In the House Conference Report, it is acknowledged that lenders were not using the buydown program. Hence, the Agricultural Credit Act of 1987 attempted to encourage greater participation in this program. This included (1) an extension of the program from September 30, 1988 until September 30, 1993; (2) the General Accounting Office (GAO) was directed to conduct an evaluation of the interest buydown program whereby they would survey banks as to why they were not utilizing the program; (3) GAO was directed to evaluate program eligibility and make recommendations as to encourage greater participation in debt restructuring; and (4) GAO was to evaluate administrative procedures of the FmHA guaranteed loan programs and make recommendations for improvements in time and efficiency.

To encourage greater participation in the program, cash flow requirements were reduced. Borrowers would have to show a projected cash flow after the interest rate reduction of at least 100% over a 24-month period, rather than 12 months. Also, FmHA county supervisors were required to make available to farmers, upon request, a list of approved lenders that participate in FmHA's guaranteed loan program [Reference House Report no 100-295].

The Omnibus Budget Reconciliation Act of 1990 [P.L. 101-508] made substantial changes to the interest assistance program. The requirement of a matching reduction in the interest rate by lenders was deleted and the amount of the subsidy provided was increased from 2 to 4 percentage points. Also eliminated was the 3-year term of assistance making interest assistance only available in 1-year increments. And the program was extended to September 30, 1995. The program was later extended to September 30, 2003 by the Freedom to Farm Act [P.L. 101-127] of 1996 before being made permanent by the Farm Security and Rural Investment Act of 2002.

Interest Assistance Usage

Interest assistance with FSA guaranteed loans has been used by lenders to lower the cost of borrowing for their clients since 1985. Interest assistance was originally made available for farm ownership (FO) and operating (OL) guaranteed loans. However, since 1991 the policy has been to target interest assistance to OL loans. The primary reason for this change in policy is the large subsidy associated with FO interest assistance loans because of the long-term nature of these loans.

The numbers of FO guaranteed loans and those that received interest assistance are shown in Figure 1. The number of FO guaranteed loans increased from 415 in 1985 to 2930 in 1993. The percentage of these loans that received interest assistance also increased from 4.8 percent in 1985 to 17.9 percent in 1991. The change in policy away from interest assistance for FO loans can be seen by the sharp drop in the number of these loans with interest assistance from 1991 to 1992. Since the interest assistance program is targeted to the guaranteed OL loan program, the rest of the paper will focus on OL loans.

The numbers of OL guaranteed loans and those with interest assistance are shown in Figure 2. There are many more guaranteed OL loans than guaranteed FO loans made in a year. The number of guaranteed OL loans has varied over the years. The largest number of loans, 14,166, was made in 1986, one year after the program was emphasized. The fewest number of loans was 8,144 in 1998. Only 0.8 to 3.6 percent of guaranteed OL loans received interest assistance from 1985 to 1990. However, the 1990 Act's removal of the lender requirement to match interest assistance and the increase in federal interest assistance from two to four percentage points spurred an increase in program usage in 1991. Since 1991 at least 12.4 percent of guaranteed OL loans have received interest assistance with 38.8 percent receiving interest assistance in 2000.

The regional numbers of guaranteed OL loan interest assistance are presented in Table 1. The Lake States, Corn Belt, and Northern Plains regions have received the most guaranteed OL loans with and without interest assistance. However, the percentages (19.02, 20.34, and 22.22) of guaranteed OL loans that received interest assistance in those three regions are nearly twice that of the next highest region (10.15). The Pacific, Delta States, and Southeast regions only had 063, 0.76, and 1.16 percent of their guaranteed OL loans receive interest assistance. Additional investigation of the potential sources of regional variation in the interest assistance program is needed.

One characteristic about the borrower in the data is if the borrower is an SDA farmer, beginning farmer, or neither SDA or beginning farmer. FSA began recording SDA and beginning farmers that received guaranteed loans in 1991 and1994. But few SDA farmers were recorded in 1991 and 1992. Therefore, data on SDA and beginning farmers for 1993 through 2002 are presented in Table 2. As would be expected since FSA targets a portion of interest assistance funds toward beginning farmers, a greater percentage of non-SDA, beginning farmers that received a guaranteed OL loan also received interest assistance (23.02 percent) than did non-beginning and non-SDA farmers (20.90 percent). However, it was surprising to see that lesser percentages of non-beginning, SDA farmers (15.92 percent) and beginning, SDA farmers (15.61 percent) received interest assistance than did non-beginning, non-SDA farmers (20.90 percent). Further analysis is needed to explain these differences.

Table 3 contains data on type of lender making guaranteed OL loans and guaranteed OL loans with interest assistance. By far the lender category with the most guaranteed OL loans is Commercial Banks with 86,500 loans for 1993 through 2002. The next largest category is the Farm Credit System with 15,148 loans, followed by the Other category with 1,314 loans, Savings and Loans with 1,252 loans, Credit Union with 641 loans, Mortgage Company with only 65 loans. Although Credit Unions did not make that many guaranteed loans, it is interesting to note that 45 percent of those loans received interest assistance, almost twice the percentage of all other lender categories.

It is interesting to see if interest rates on guaranteed OL loans not receiving interest assistance are similar to interest rates on those loans receiving interest assistance (borrower charged rate plus interest assistance rate). Figure 3 shows the average interest rates that lenders were to receive for non-interest assistance loans and interest assistance loans and the difference in these two rates for 1985 through 2002. Notice that the non-interest assistance rate is approximately two percentage points more than the interest assistance rate for 1985 through 1990. After 1990 there is hardly any difference between the two rates. This can be explained by the 1990 Act that removed the up to two percentage point interest rate match requirement. It appears that since 1990 lenders are charging about the same rate of interest on guaranteed loans, whether the interest is charged just to the borrower as on guaranteed loans without interest assistance or the interest is charged both to the borrower and FSA as on guaranteed loans with interest assistance.

The data presented in Table 4 shows the FSA guarantee percentage for guaranteed loans. The vast majority of guaranteed OL loans (90.85 percent) are written at a 90 percent guarantee. An even higher percent of guaranteed loans with interest assistance (94.50) are written at the 90 percent guarantee. Also note that 41.75 percent of the guaranteed loans with more than a 90 percent guarantee received interest assistance.

Figure 4 shows the percent of guaranteed OL loans made in a given year that had at sometime claimed a loss by March 2003. The loss claim percentages are for non-interest assistance loans and interest assistance loans. The percent of loans claiming a loss have trended downward over the period. But much of this downward trend in loss claim rates is likely the result of the loans made in recent years have not had enough time to incur and claim a loss. The loss claim percentage is greater for non-interest assistance loans than interest assistance loans in every year. This may indicate that the interest assistance program is successful in assisting farmers repay their loans. However, the intent of the program may be to allow farmers that qualify for interest assistance to have the same success with repaying loans as those farmers with guaranteed loans that do not qualify for interest assistance.

Figure 5 shows the percent of guaranteed OL loans made in a given year that are still active as of March 2003. There is an upward trend in the percent of active loans since more recent loans have not had as much of an opportunity to be repaid or incur a loss as the loans made in earlier years. A higher percentage of guaranteed loans with interest assistance are still active in every year than guaranteed loans without interest assistance. Besides differences in loss claim rates, another potential reason for the difference in active status is that farmers are less likely to pay early on below-market rate, interest assistance loans than on at-market rate, non-interest assistance loans.

Summary

The Farm Security and Rural Investment Act of 2002 made permanent the interest assistance program for the Farm Service Agency's guaranteed loans, authorized a significant increase in funding for the program, and targeted funding for beginning farmers and ranchers. The research presented here provided a basic descriptive analysis of past use. In particular, borrower data for Federal fiscal years 1985 through 2002 were examined in several dimensions. These dimensions included geographic, borrower type, lender type, interest rate differentials, percent guarantee, and the status of the loan as to whether a loss claim was paid or the loan remained active.

Even though the program has been in existence for more than 15 years, little is known about its impact and utilization. This research is an initial step in documenting usage of the program. More detailed analysis is needed to explain regional variation, borrower type, and lender type usage. Also, additional research is needed to explain interest assistance program successes and losses at the loan level.

Table 1. Guaranteed OL Loans by Region, 1985-2002

Regions	IA	Total	Percent IA
Northeast	722	7,347	9.83
Lake States	5,437	28,587	19.02
Corn Belt	8,896	43,733	20.34
Northern Plains	7,864	35,391	22.22
Appalachian	1,059	11,568	9.15
Southeast	91	7,874	1.16
Delta States	149	19,509	0.76
Southern Plains	2,143	21,122	10.15
Mountain	1,024	11,087	9.24
Pacific	43	6,857	0.63

IA = Interest Assistance Loans

Table 2. Guaranteed OL Loans by Borrower Type, 1993-2002

Borrower Type	IA	Total OL Loans	Percent IA
BF Only	2,564	11,139	23.02
SDA Only	503	3,159	15.92
BF & SDA	130	833	15.61
Non-BF, Non-SDA	18,778	89,868	20.90
Total	21,975	104,999	20.93

BF = Beginning Farmer
SDA = Socially Disadvantaged Farmer
IA = Interest Assistance Loans

Table 3. Guaranteed OL Loans by Lender, 1993-2002

Lender Type	IA	Total OL Loans	Percent IA
Commercial Bank	19,841	86,500	22.94
Farm Credit System	2,111	15,148	13.94
Savings and Loans	217	1,252	17.33
Credit Union	290	641	45.24
Mortgage Company	5	65	7.69
Other	91	1,314	6.93
Total	22,555	104,920	21.50

IA = Interest Assistance Loans

Table 4. OL Loans by Percent Guarantee, 1985-2002

Percent Guarantee	IA	Total	Percent IA of Total	IA as Percent of IA Column Total	Total as Percent of Total Column Total
<60	6	227	2.64	0.02	0.12
60-69	8	1,644	0.49	0.03	0.86
70-79	300	5,983	5.01	1.09	3.12
80-89	958	9,135	10.49	3.49	4.76
90	25,923	174,434	14.86	94.50	90.85
>90	238	570	41.75	0.87	0.30
Column Total	27,433	191,993	14.29		

IA = Interest Assistance Loans

Figure 1. Guaranteed FO Loans

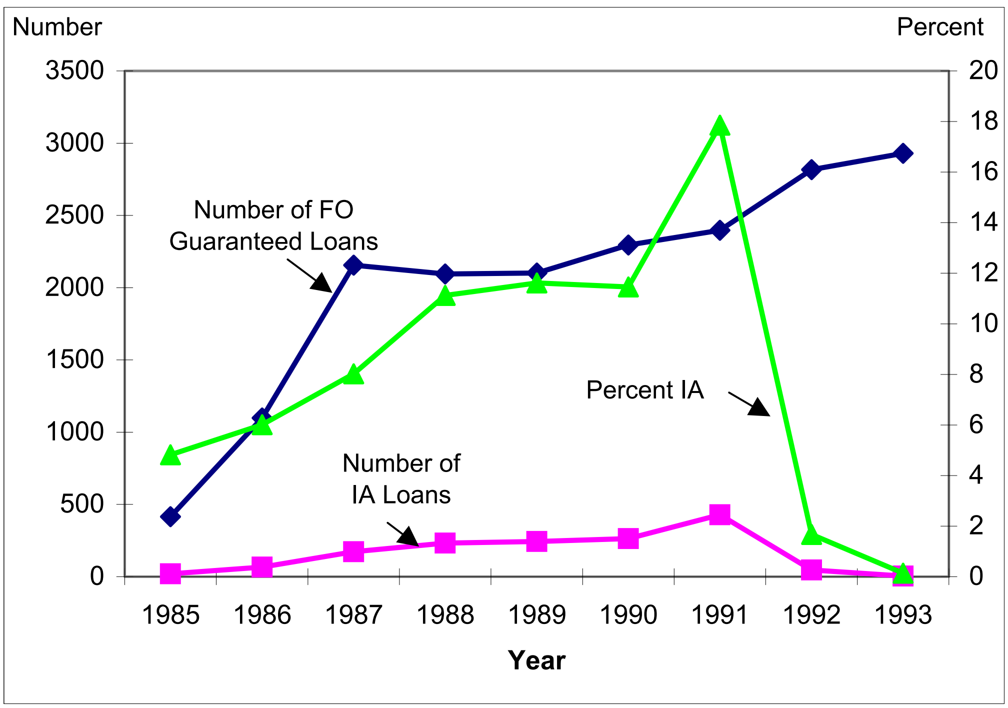


Figure 2. Guaranteed OL Loans

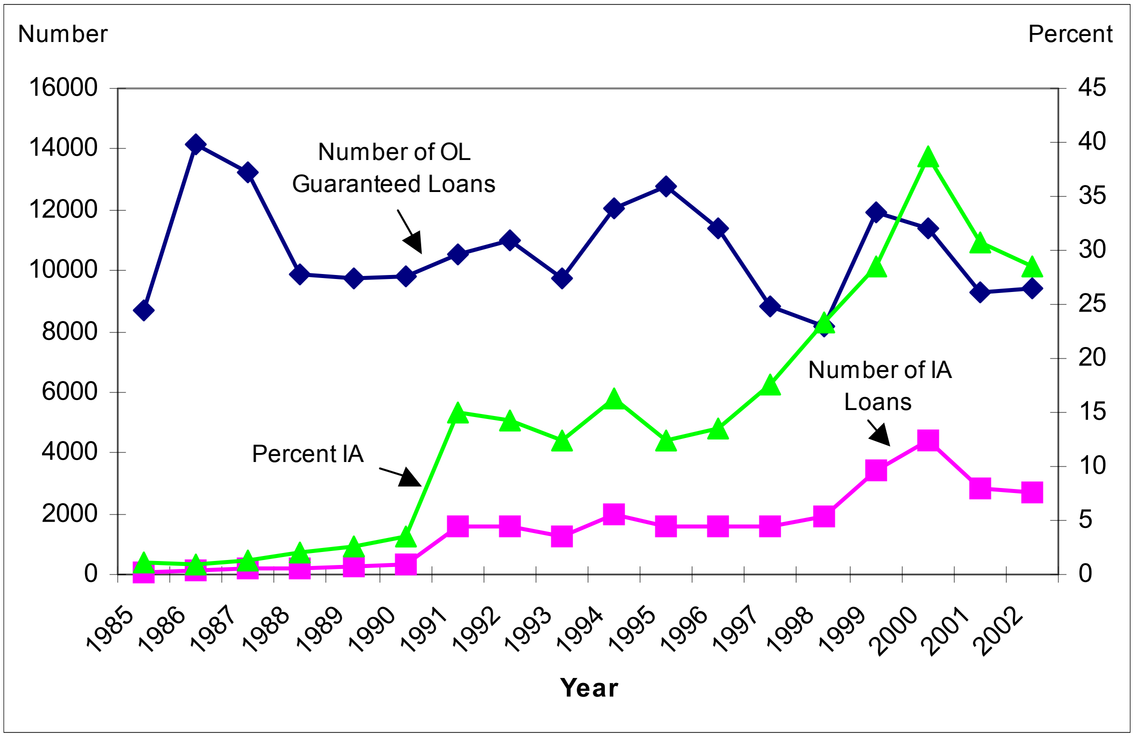


Figure 3. OL Interest Rate Average

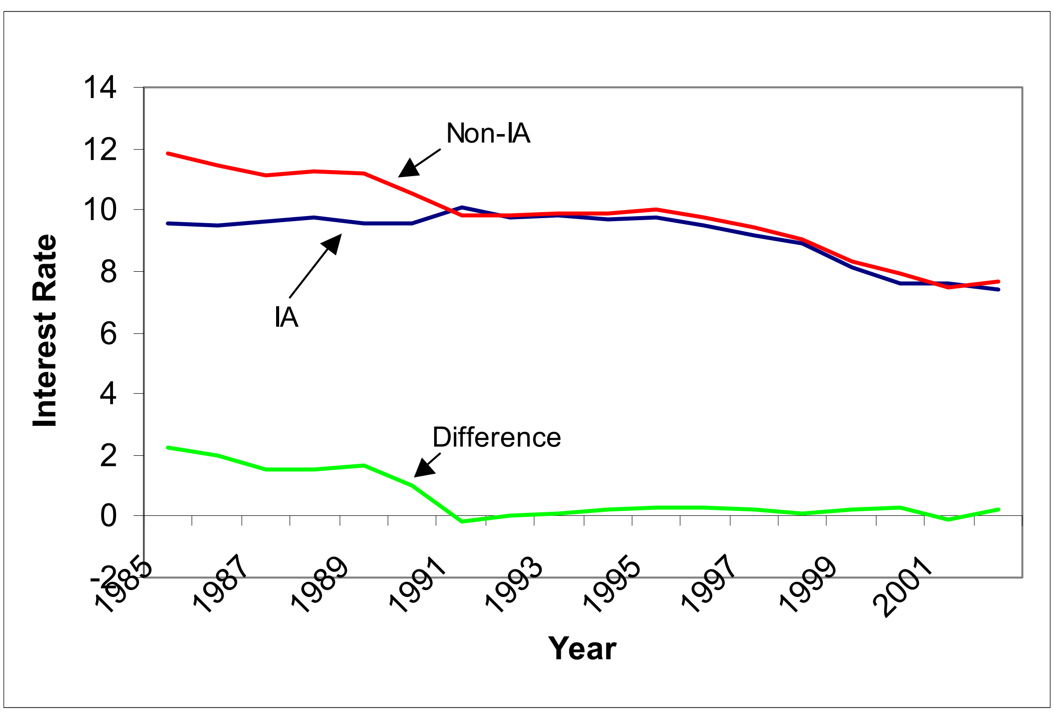


Figure 4. Percent of Guaranteed OL Loans Claiming Loss

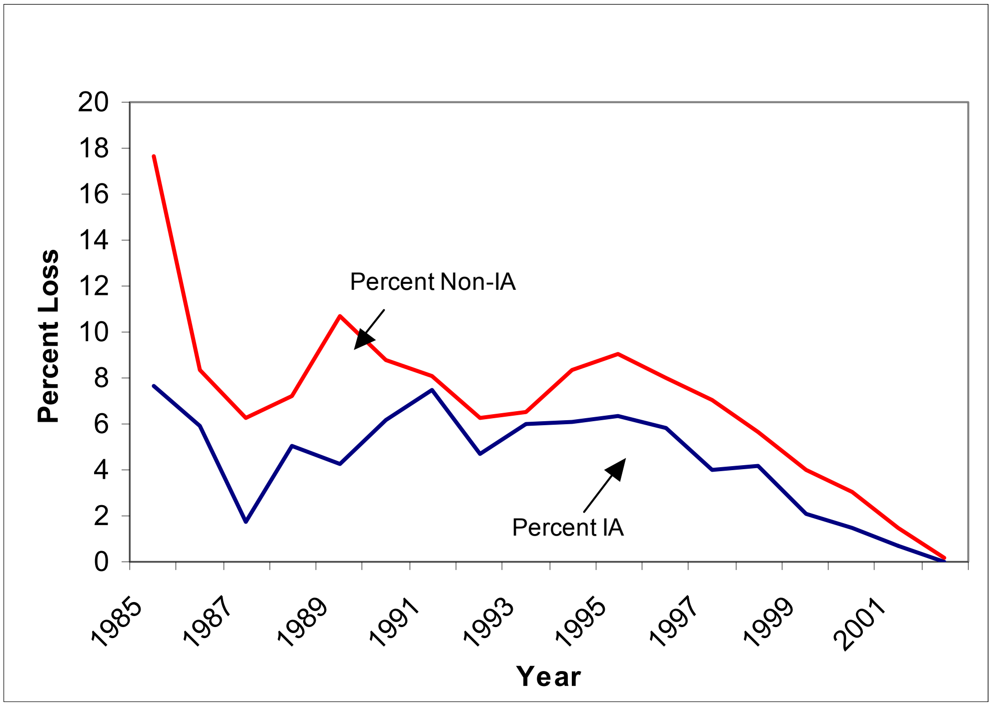
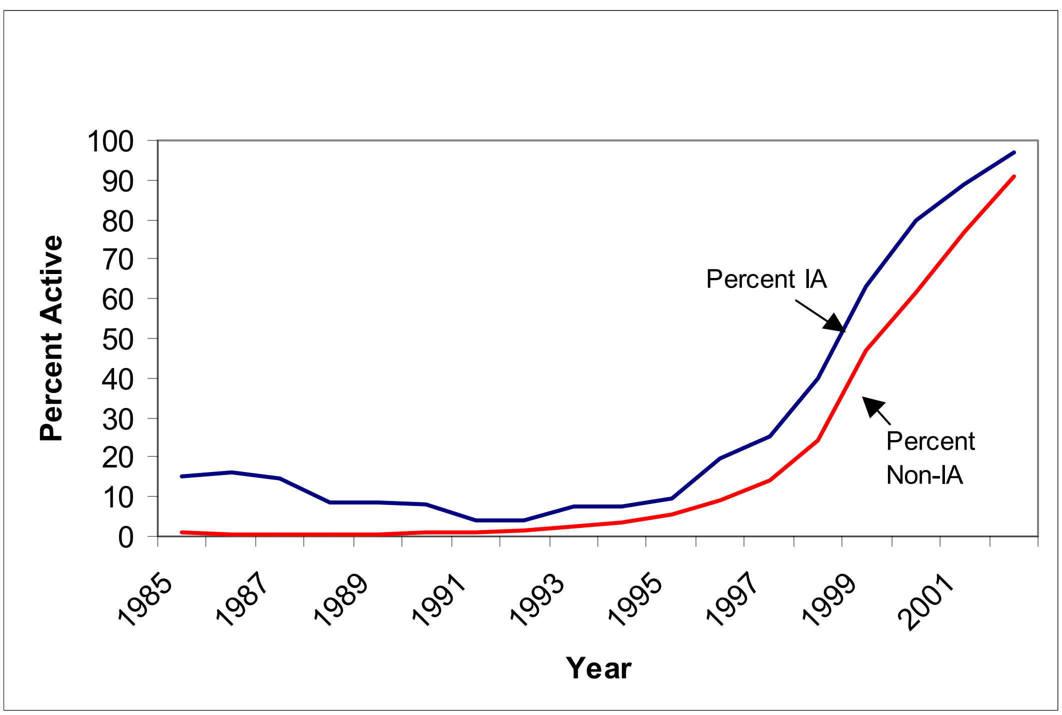


Figure 5. Percent of Guaranteed OL Loans Active



Analysis of Market Segmentation in Farm Credit Markets

By Charles B. Dodson and Steven R. Koenig[1]

Abstract:

Agricultural credit markets are dominated by two institutional retail lender groups, the cooperative Farm Credit System (FCS) and commercial banks. Together these two lender groups supply 70 percent of the farm sector's total credit needs. This analysis uses USDA's 2001 and 2002 Agricultural Resource Management Survey to examine whether these two lender groups were serving different segments of the farm credit market. Regulatory, legislative, structural, and competitiveness factors are expected to influence market segmentation. National estimates made using a binomial logit model indicate that the National farm credit market is segmented. When compared to commercial bank lending in 2001 and 2002, the FCS's lending was more focused on full-time commercial farms that were less heavily indebted, more profitable, and had greater debt repayment capacities. The FCS was also more likely to supply credit to young and beginning farmers and to farms located in areas having access to a FCS office, but where few agricultural banks were located.

Keywords: Agricultural Credit Markets, Market Segmentation, Farm Credit System, Agricultural Banks, and Farm Lenders.

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Analysis of Market Segmentation in Farm Credit Markets

Commercial banks and the cooperative Farm Credit System (FCS) are the primary suppliers of agricultural credit. These two lender groups supplied over 70 percent of total farm business debt at the end of 2002 (USDA 2003). Because of their large market shares, the lending policies and procedures of these two lender groups should have a considerable influence on overall credit availability to farmers and ranchers.

Market segmentation describes the division of a market into homogeneous groups in order to focus on customers most likely to purchase products or services offered. If done properly, market segmentation can enhance a firm's competitive advantage and improve market efficiencies. On the other hand, market segmentation may result in less competitive delivery of products or services to groups identified by lenders as more costly to serve. Structural change in agricultural production when coupled with the deregulation of financial markets and information technologies advancements have significantly improved the ability of lenders to segment farm credit markets. In this analysis, we use a logit model to analyze the extent to which the two primary farm lender groups, the FCS and commercial banks, are serving different segments of the farm credit market in 2001 and 2002.

Market Segmentation and Farm Credit Markets

Market segmentation was first described in the 1950's, when product differentiation was the primary marketing strategy. In the 1970's and 1980's, firms used market segmentation to expand sales and obtain competitive advantages in the market place (Wedel and Kamukara). Improvements in information technology during the 1990's provided businesses with more sophisticated and lower cost techniques to identify and reach potential customers with more customized offerings of goods or services. For example, many lenders now use credit-scoring techniques to better segment borrowers.

To segment markets effectively there must be significant and measurable differences among customers. Demographic variables such as age, sex, race, income, occupation, education, household status, and geographic location can be used to segment markets. Historically, agricultural lenders have used location, enterprise type, loan size, or credit risk as a basis for segmenting credit markets (Boehlje). For some lenders, market segmentation may also use psychographic variables such as life-style, activities, interests, and opinions. Each group represented in a market segment must seek unique benefits and the marketer must be able to provide products or services that address such needs.

Some past research has identified farm credit market segments 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 the farm lending market. Moss et al. used a similar criterion to describe three potential market segments consisting of large-scale producers, small-scale producers, and industrial units. Both studies indicated the credit needs of part-time farmers are different from the credit needs of full-time commercial farmers.

In recent years, financial markets have undergone fundamental changes that have enhanced the abilities of lenders to undertake market segmentation. Besides technological advances that have increased the availability of information and lowered transaction costs, financial deregulation has increased competition and prompted consolidation by removing geographic and industry barriers (Executive Office of the President). Financial institutions are now better able to focus on market segments or niches in which they have the greatest competitive advantage. Nonbank financial institutions have increased their presence by providing financial products not previously available. Internet based financial services have lowered financial transaction costs and reduced the importance of physical location.

While these advances should greatly enhance the overall efficiency of credit markets, some groups may be less likely to benefit. For example, credit scoring may be difficult to apply to some market segments with unique characteristics that are difficult to standardize. And some lenders may limit lending to market segments that are not easily scored. On the other hand, credit scoring may be better suited for quantifying risk for smaller farm loans where repayment is based mostly on non-farm earnings. These loans are more similar to consumer loans and, therefore, may be more easily standardized.

Farmers in more sparsely populated areas may have fewer lender choices, and therefore, are more likely to face imperfect competition for their loans than their counterparts in more urban areas (USDA 1997). The financial deregulation over the past couple decades spurned consolidation in commercial banking with the number of banks dropping from over 14,000 to just 7,800 in 2002. The FCS has experienced similar changes with the number of associations dropping from over 800 to under 100. The fear is that larger financial institutions may focus more on large customers and business lines that utilize economies of scale and scope, leaving smaller borrowers, especially those in more rural areas with more limited credit sources.

In this analysis, we examine the segmentation of the agricultural credit market by FCS lenders and commercial banks in 2001 and 2002. There are several reasons to expect that the FCS and banks might serve different market segments. Statutes and regulations restrict eligibility to FCS loans and limit the types of financial products it may offer. While banks may geographically segment markets, the FCS is expected to provide access to their services in all counties of the US. Banks and FCS have very different organizational structures that may impact the market segments chosen to target.

Past research using USDA's Agricultural Resource Management Survey (ARMS) has shown that different groups of lenders tend to serve different segments of the farm credit markets. Dodson and Koenig (1994) using 1991-2 data found the FCS concentrated its lending most heavily among larger, older, wealthier, and higher income operators. Using 1997 data, Ryan and Koenig (1999) found similar results, showing that FCS debt was concentrated in larger farming operations that were more financially secure. Ryan and Koenig (2001) using 1999 data reaffirmed the earlier studies.

Regulations and Market Segmentation

The Farm Credit Act of 1971 requires the FCS to serve *bona fide farmers and ranchers.* Regulations define a bona fide farmer or rancher as a person owning agricultural land or engaged in the production of agricultural products, including aquatic products under controlled conditions [US Code 12CFR613.3000]. This can include both full and part-time farmers, as well as nonfarming landlords. Also, regulations stipulate that FCS institutions provide full credit, to the extent of creditworthiness, to full-time bona fide farmers for agricultural enterprises [US Code 12CFR613.3005].

FCA regulations limit the type of financial services which FCS institutions may provide. Such related financial services offered include tax preparation, leases, and consulting and appraisal services. Unlike a full service bank, FCS lenders may not directly provide services such as checking, investments, or business loans not related to farming. Compared to part-time farms, operators of commercial-size farms are more likely to benefit from the financial products and services provided by FCS, such as consulting and appraisal services, or the agricultural knowledge and expertise an FCS loan officer may provide. While there are no explicit limitations on providing credit to part-time farmers, current FCA regulations clearly limit this activity. Scope requirements stipulate that FCS lenders are to provide only "conservative" credit to part-time farmers.

Commercial banks have no specific regulations governing which segments of the credit market they serve. However, the Community Reinvestment Act (CRA) encourages 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 of greater CRA reporting requirements imposed on them. Also, banks are more likely to have a comparative advantage over the FCS in meeting the needs of part-time farmers because they can provide a wider array of financial services. 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 provided. Thus, Federal laws and regulations establish an environment where the FCS is more likely to serve full-time farms while banks are more likely to serve small or part-time farms.

Impact of Lender Competition on Market Segmentation

The FCS was established by Congress to ensure that farmers in all areas of the US had access to farm credit.[2] FCS branch offices are geographically dispersed, with offices located in 48 of the 50 States. Only Alaska and Rhode Island do not have a FCS branch office within their borders. With the exception of more remote areas, all counties in the US are within 50 miles of a FCS branch office (Figure 1). Even some of those areas or counties without a branch office may be served through contact points, which are staffed by FCS only on designated days.

[2] The Farm Credit Act of 1971 specifies that all counties and municipalities in the US and Puerto Rico should have access to FCS credit.

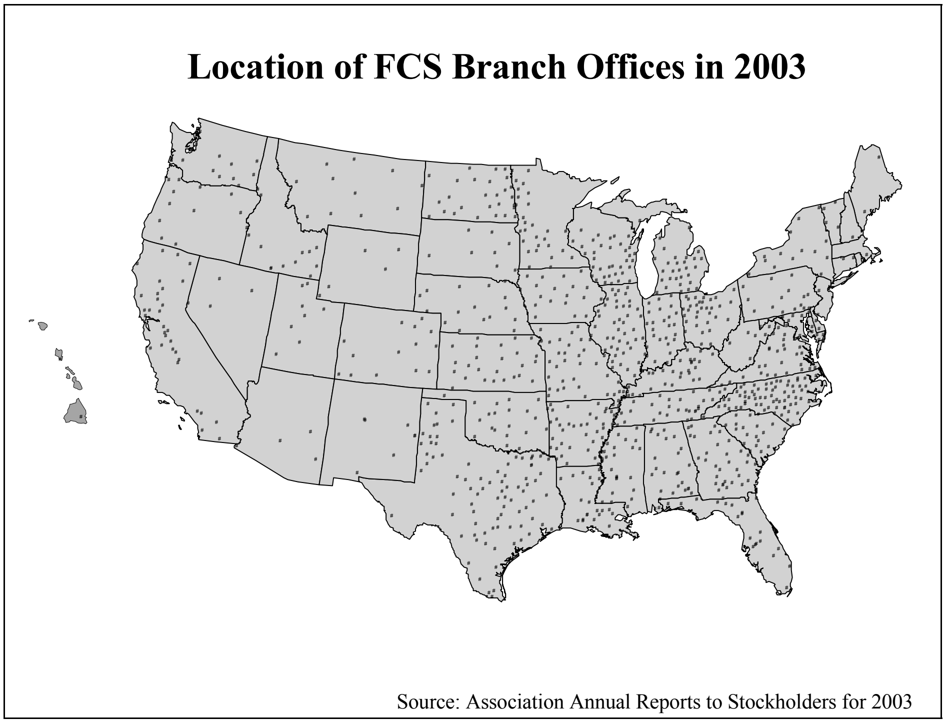

Figure 1. FCS Branch Offices Dispersed Throughout U.S.

In contrast to the FCS, banks are not required to serve all U.S. counties and municipalities. Consequently, banks may be reluctant to provide agricultural credit in areas with limited farm borrowers or depressed economic conditions. Hence, farm borrowers in such regions may face less competitive farm loan markets because of a limited presence of banks that make agricultural loans. Banks that specialize in agricultural lending (at least 10 percent of the total lending to agricultural businesses) are heavily concentrated in the Corn Belt and central plains States, where agriculture represents a larger portion of total economic activity (Figure 2). Farmers located in these regions are likely to have access to multiple agricultural bank branches within a relatively short geographic distance, while farmers in the Northeast, Mid-Atlantic, Southeast and Mountain States may have no agricultural bank branches within their county or in a nearby location. In those areas with few alternative farm lenders, the FCS is more likely to have a larger market share.

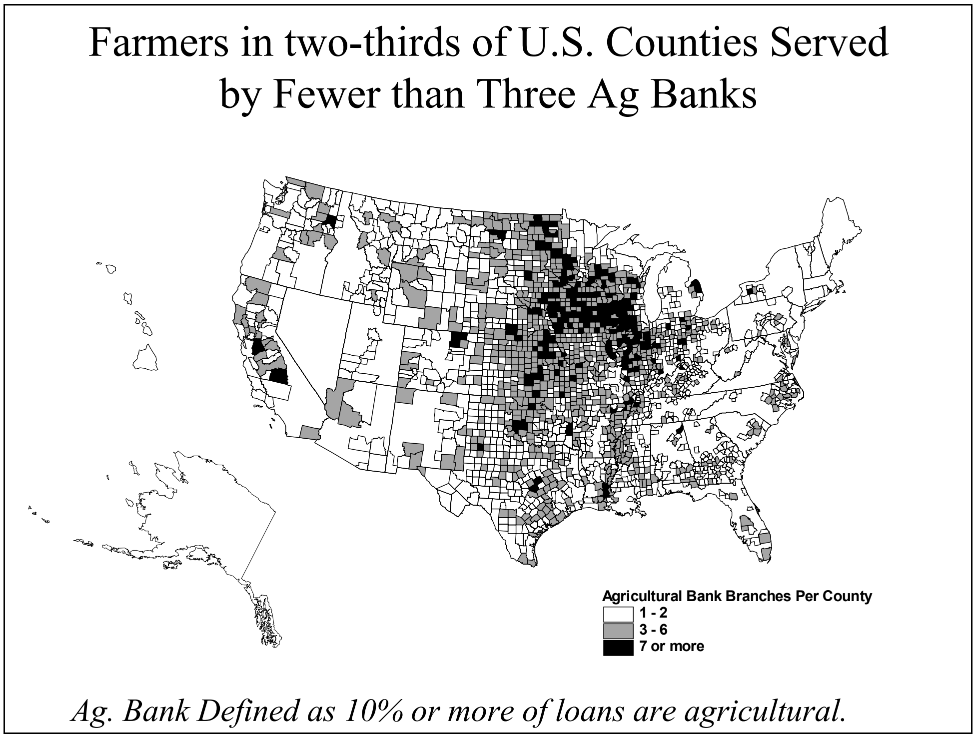

Figure 2. Branches of Agricultural Banks Concentrated in Midwest.

The financial health of small or community commercial banks is closely linked to the economic condition of the region they serve. Even with CRA requirements, banks might be reluctant to provide farm or nonfarm credit in economically depressed regions. The FCS, on the other hand, is less able to exercise such geographic segmentation. One measure of regional economic well being is median household income. Not surprisingly, the median household income tends to be highest in metro regions and lower in rural areas. Some of the lowest household incomes occur in Appalachia, the Delta, and the Ozarks. The expectation is that banks would be less active in providing business loans in counties with lower household incomes. Consequently, borrowers located in these counties might be more likely to borrow from FCS institutions.

Impact of Lending Structure on Market Segmentation

The organizational structure of lending institutions may affect the market segments they serve. The FCS is a borrower owned cooperative with government sponsored enterprise (GSE) status whereas commercial banks are investor owned firms. These differences affect how they are managed. Banks seek to maximize returns to stockholders while cooperatives, theoretically, seek to minimize member's borrowing costs.

Relative to the FCS, banks typically have a much more diversified investment or loan portfolio. As a consequence, bank managers may be less concerned about the relative risk associated with lending to agricultural enterprises and therefore may more easily adopt underwriting standards that are less stringent than that of a FCS lender. Also, banks may profit from other business relationships with the borrower, which could foster less concern about the risk associated with an agricultural loan. FCS associations are primarily invested in agricultural loans and are much more sensitive to unsystematic risk, which could lend to a more conservative lending approach than banks. On the other hand, by specializing in agricultural loans, FCS managers may be more capable of identifying and managing farm lending risks, which could result in a less conservative lending approach than banks.

Differences in regulatory structure may also influence market segmentation. FCA examiners are focused only on FCS institutions, and therefore are well acquainted with the risks and issues affecting agricultural lending. Bank examiners, on the other hand, may have less expertise concerning agricultural loans. The greater expertise of FCA examiners may result in the FCS being more thorough in their loan making decisions and able to satisfy regulator concerns on higher risk loans. A more limited understanding of agricultural businesses by bank examiners may discourage banks from making higher risk farm business loans. In addition, banks face different regulatory systems depending on the nature of their bank charter and hence face potentially different review systems.

The different governance and regulatory structure for banks and the FCS could result in differences and underwriting criteria and lending policy. Though, it is difficult to predict, a priori, the direction of these impacts. Nonetheless, the expectation would be that these differences could impact the market segments served by banks and FCS.

Impact of Targeting on Market Segmentation

To assure that presumed undeserved groups within society have access to credit, Congress has instituted policies requiring certain lender groups 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 that increase service to young, beginning, and small farms (YBS). In recent years, FCA has placed increased emphasis on enforcing this part of the FCS's legislative mission. A FCA Policy Statement issued in 1998 said, "Each Board of Directors within 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 the housing GSE's; the directive has lead to increased public reporting requirements and greater YBS program development and use (68 Federal Register 53915, September 15, 2003).

While banks have no specific targeting requirements they can be subject to the Community Reinvestment Act, which encourages lending to underserved credit markets, such as those in urban centers. While the FCS and banks are prohibited from practicing discrimination in lending, there is no specific regulatory requirement for either the FCS or banks to serve racial or ethnic minority farmers. Yet, many regions with a greater presence of racial and ethnic minorities are characterized by lower incomes. Such characteristics might discourage bank lending to farms in these counties. However, the FCS is directed to serve all farm borrowers with a basis for credit, regardless of location, which could increase the likelihood that racial and ethnic minorities are served by FCS institutions relative to the banking industry.

The Model

The estimated model's null hypothesis is the attributes of borrowers receiving FCS loans is not different from those receiving commercial bank loans. Alternatively, any difference in borrower attributes between the two lender groups is indicative of market segmentation. Multivariate techniques such as clustering, conjoint analysis, or factor analysis are commonly used to identify and create post hoc market segments. For determining the a priori existence of market segments, logit, probit, or discriminate analysis is commonly used (Wedel and Kamukara). Black and Schweitzer used multinomial probit analysis to determine whether home mortgage markets were segmented among commercial banks and mutual savings. Based on the level of significance for the model's summary statistics, Black and Schweitzer concluded that home mortgage markets were segmented. In this analysis, 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 would be considered to be consistent with the presence of market segmentation.

This study utilizes data from the 2001 and 2002 Agricultural Resource Management Survey. The ARMS is USDA's primary vehicle for data on a broad range of issues about agricultural resource uses and costs, and farm financial conditions.[3] Financial and demographic data for farms obtaining loans from a commercial bank or a FCS institution during 2001 and 2002 was selected for this study. The dependent variable, Y, is equal to 1 if a majority of the farm operator's debt originated during this period was provided by FCS, 0 if the majority was from banks.[4] As such, a Y equal to 1 would correspond to the group of farmers included in the FCS market segment, while a Y equal to 0 would correspond to one in the bank market segment.

The expectation as to which particular segment a borrower belongs is hypothesized to be a function of a set of factors related to the regulatory environment, the competitiveness of local credit markets, lender organizational structure and governance, and borrower targeting requirements (table 1).

Y= *f* (regulatory factors, competition, organizational and governance, targeting requirements).

Regulatory Factors

Regulations governing eligibility for FCS farm loans should increase the likelihood that FCS borrowers are full-time or commercial-sized farmers and reduce the likelihood that its borrowers are part-time or hobby farms. FCA regulations state that "loans to farmers shall be on an increasingly conservative basis as the emphasis moves away from the full-time bona fide farmer to the point where agricultural needs only will be financed for the applicant whose business is essentially other than farming. Credit shall not be extended where investment in agricultural assets for speculative appreciation is a primary factor" (12CFR 613.3005).

[3] For more information on ARMS see Mishra et al, Appendix A.

[4] Majority of debt is defined as a borrower having at least 50 percent of their total debt from a particular lender group. Ryan and Koenig (2001) have shown that most borrowers rely on one lender for their credit needs.

FCA provides no absolute definition of full-time or part-time farms. However, past research 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 et al.) In order to identify full and part-time farmers five mutually exclusive categories were developed for the model (table 1).

A large full-time commercial farmer (FULLTIME) was defined as one who considers farming to be their primary occupation, is fully employed by the farm business, is reliant on the farm business for most of their family income, and has annual farm sales of greater then $250,000. This market segment would most likely be a full-time bona fide farmer and not a part-time farmer. In addition, these full-time farms are most likely to benefit from the FCS's credit programs, its expertise, and its farm related services.

Table 1. Variable names, description, and expected influence on outcome.

Variable name	**Description**	**Lend -er**
FULLTIME	Large full-time commercial farm. 1, if primary occupation is farming, annual operator labor hours over 1,500, over 50 % of household's income is from farm business, and annual sales over $250,000; 0 otherwise.	FCS
FAMFARM	Family-size commercial farm. 1, if not considered a large full-time commercial farm, primary occupation is farming, annual operator labor hours over 1,500, and sales over $100,000; 0 otherwise.	Both
OTH_COM_FM	Other commercial-size farm. 1, if annual sales over $100,000 and not considered either large or family-size commercial farm as previously defined; 0 otherwise.	Bank \1
PARTTIME	Part-time farm. 1, if primary occupation is farming, annual sales under $100,000, annual operator labor hours ≥ 1,000 hours, and median household income < 200% of county median; 0 otherwise.	Bank
HOBBY	Hobby or lifestyle farm. 1, if annual sales under $100,000 and not considered as part-time; 0 otherwise.	Bank
COMPETITION	Lending competition. 1, if farms is located in a county where there is less than 3 bank branches making agricultural loans and an FCS branch located within 20 miles of the county line; 0 otherwise.	FCS
FARM_SHR	Measure of farming's importance to economy. Share of total population residing on farms.	FCS
MED_HHI	Median county-level household income. 1, if county average household income less than $32,000; 0 otherwise.	FCS
DA RATIO	Solvency. Total year-end debt plus production loans repaid divided by year-end assets plus the amount of production loans repaid during the year.	*A/*
TDBTCOV	Debt capacity. Term debt coverage ratio.	*B/*
PMARGIN	Profitability. Profit margin.	*B/*
CAPITAL	Capitalization. Net worth per dollar of annual sales.	*B/*
VULNERABLE	Financial vulnerability. 1, if total household income is below poverty level and debt-to-asset ratio greater than 0.40; 0 otherwise.	*A/*
RACE_ETHNIC	Racial and ethnic minority. Share of total farm resident population in county that is a member of racial or ethnic minority group.	FCS
BEG_YOUNG	Young or beginning farmers. 1, if primary operator under 36 years of age or has less than 10 years of farming experience; 0 otherwise.	FCS
OVER_55	Older farmers. 1, if primary operator > 55 years of age; 0 otherwise.	Bank

\1 Variable omitted from model for estimation. *A/*, *B/* There is no a priori expectation concerning underwriting standards. It expected that directional impacts to be consistent among those designated /*A* and /*B*. That is, if those borrowing from banks <the FCS> had higher debt-asset ratios, banks would also be expected to serve more financially vulnerable borrowers. Those borrowing from the FCS < banks> that had greater capitalization would also be expected to have greater profitability and debt capacity.

A family-size commercial farm (FAMFARM) had annual sales of at least $100,000 and the primary operator either considered their primary occupation to be farming or supplied at least 20 hours of labor per week to the farm business. Most within this group would likely be considered full-time bona fide farmers, though some may be considered part-time farmers. The expectation is that family-size commercial farms might be more likely to borrow from the FCS rather than from banks. The other commercial farm group (OTH_COM_FM) is a residual segment and includes those commercial farms for who the primary occupation is not farming and report less than 1,000 hours of annual operator labor hours. This group is expected to be more likely to borrow from banks, but for purposes of empirical estimation this variable was omitted.

Part-time farms (PARTTIME) were defined as those with annual farm sales of less than $100,000, where the primary operator considered their primary occupation to be farming, and the operator indicated he or she supplied less than 20 hours of labor per week to the farm business. Also, the household income of the operator was less than twice the county average. The part-time farmer group is structured to capture small farms that are likely to be operated as a farm business rather than as a hobby or lifestyle farm. While some within this group may still meet the regulatory requirement of being a full-time bona fide farmer, it is also likely that many may find the array of nonfarm related financial services provided by banks more important to their needs than the farm related financial services of the FCS. Therefore, 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), include all those with less than $100,000 in annual sales that were not already defined as part-time. Operators of hobby farms would be considered least likely to be considered full-time bona fide farmers and FCS is suppose to be providing only “conservative” credit to this group. This borrower group is most likely to fall into the bank market segment.

Farm Credit Market Competitiveness

While the FCS’s mandate is to serve farmers nationwide with a basis for credit, commercial banks with agricultural lending expertise can avoid regions or counties where farm lending volumes are low or unprofitable. In geographic regions where agriculture production is sparse or where there are competing investment options for banks, the local farm credit market is more likely to be less competitive. Farmers residing in such counties would be more likely to turn to the FCS for their credit needs.

To measure farm credit market competitiveness, a variable (COMPETITION) was constructed which identified counties where few agricultural banks have a presence. Using commercial bank call report data, branches of banks having at least 10 percent of their total loans to agriculture were identified. Using Annual Reports to Stockholders, FCS association branches were also located. The number of agricultural bank branches per county and FCS association branches per county were then estimated.[5] This information was used to construct the leading competition variable. The variable had a value of 1 if the farm was located in a county where

[5] The Call Report data and FCS Association Annual Reports provided information on the mailing address of each branch. Using zip codes, the software application ArcView could approximate the geographic location of each agricultural bank and FCS association branch. By using the ArcView query procedure, bank or FCS branches per county were subsequently determined. A county was considered to have access to a FCS branch if it was located either within the county or within 20 miles of the county line.

there are less than 3 bank branches making agricultural loans and an FCS branch located within 20 miles of the county line. It was expected that for observations where the value was 1, the borrower would be more likely to fall into the FCS market segment.[6]

Relative to the FCS, banks may be more conservative in their provision of credit to economically distressed regions. As a profit-maximizing firm, banks usually focus their lending efforts in areas that offer the greatest profits, which is less likely to include economically distressed regions. The county's median household income was used as an indicator of economic well-being (MED_HHI). Farms located within counties where the median household income was in the two lowest national quartiles (less than $32,000) would be considered more likely to fall within the FCS market segment.

In many counties throughout the U.S., there is not enough demand for farm loans for lenders to justify the devotion of any resources to agricultural lending. The share of the total county population comprised by farm residents (FARM_SHR) from the 2000 Census of Population was used a measure of agriculture's relative economic importance. It was expected that among counties where farm residents comprised a larger share of the population, farmers were more likely to fall into the bank market segment. For counties where farm residents were less common, borrowers would be more likely to fall into the FCS market segment.

Structural Differences in Lending

The types of market segments served by the two lender groups should be influenced by differences in ownership and management systems. Managers and directors of the FCS and banks may have different goals and objectives concerning profit motivation and agricultural lending policies. These differences, in turn, may result in dissimilar underwriting criteria between banks and the FCS.

Financial measures for solvency, debt repayment capacity, and profitability were included in the model to reflect possible differences in lending standards between the two lender groups. Solvency (DA RATIO) was measured using the borrower's debt-to-asset 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. Repayment capacity (TDBTCOV) was measured using the term debt coverage ratio and included nonfarm sources of income. Profitability (PMARGIN) was measured using the profit margin of the business. Capitalization (CAPITAL) or farm net worth was used to measure of the ability of the farm to withstand economic downturns without any adverse consequences to the lender. Because larger farms require greater amounts of capitalization, net worth was expressed as a share of annual sales. Finally, lenders who are more risk averse would be more likely to avoid making loans to financially vulnerable farms. A farm was defined as financially vulnerable (VULNERABLE) if total household income was below the poverty level and the debt-to-asset ratio was greater than 0.40.

There is no clear expectation as to which lender group might be more likely to segment the market based on financial criteria. While the FCS may be more conservative in its lending policies due to the fact it is essentially a single sector lender and may be unable to profit from

[6] The absence of agricultural banks does not necessarily mean there are no banks making agricultural loans. A large commercial bank may have a large amount of agricultural loans, but is not considered agricultural because it does not meet the 10 percent requirement.

other financial relationships with the borrower, it may be better able to identify and manage lending risks than many bank lenders. Past research has generally supported the notion it is more conservative in its lending policies. Nonetheless, consistency among loan underwriting measures is expected. More conservative lending would result in lower debt-to-asset ratios, higher coverage ratios, greater profit margins, higher net worth, and fewer loans to financially stressed farms.

Underserved Groups

Age is a common factor used to segment markets, including financial markets. Older farmers may have a greater need for a broader span of financial services, including management of investments and estate planning. Conversely, younger or new entrants are more likely to need to borrow capital, and thus are more likely to demand credit products or related services. Yet, loans to these farmers tend to carry greater risk because of their limited capital, incomes, and credit histories. This discourages lenders from providing credit to this group.

Statute requires that each FCS association have policies and programs in place that meet the special needs of young and beginning farmers. Following FCA 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. Because of these statutory requirements it is expected that young and beginning farmers would be more likely to fall within the FCS market segment. On the other hand, farmers over 55 years old (OVER_55) are expected to fall within the bank segment because of their more varied need for financial services.

There are no specific requirements that the FCS or banks target their lending to racial or ethnic minority farmers. Yet, the FCS is expected to have a greater likelihood of serving this market segment because these groups tend be concentrated in economically distressed regions. As a National lender, the FCS is suppose to serve all farm borrowers and regions with a basis for credit, including those in economically distressed regions. 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.[7]

Results

Mean statistics indicate there were some distinct differences between the market segments being served by the FCS and commercial banks in 2001 and 2002. The FCS had a greater presence in the full-time commercial-sized farm segment relative to banks. FCS borrowers operated larger farms as indicated by the value of farm production, acres operated, and total farm assets (table 2). In addition, FCS borrowers were more reliant on the farm business than new bank borrowers, receiving 38 percent of total household income from the farm compared to only 6 percent for bank borrowers.

The statistics also suggest that FCS was serving lower risk segments of the credit market relative to banks. FCS borrowers exhibited greater solvency with lower debt-to-asset ratios and less financial stress. Yet, perhaps because of its National lending mandate, the FCS tended to serve poorer regions that had lower incomes and were more likely to have a greater presence of

[7] While ARMS provided information on the race, ethnicity, and gender of each surveyed farm, there too few observations of racial and ethnic minorities to provide reliable estimates. Therefore, Census of Population data was used to measure the presence of racial and ethnic minorities in farming.

racial and ethnic minorities. In addition, FCS market share appears to be greater in those regions that are less competitive, having fewer agricultural banks and farm borrowers. Finally, those receiving FCS loans in 2001 and 2002 tended to be younger and were more likely to be a beginning farmer than banks, suggesting that relatively new YBS rules might be influencing FCS lending decisions.

The multivariate logit analysis largely confirmed these differences between FCS and bank borrowers, both individually and collectively. Each of the standard summary statistics were significant at the 0.0001 level indicating that FCS and bank borrowers were segmented on at least one of the attributes included in the model (table 3). The results indicate that most individual parameter signs are significant and are as expected. The c statistic estimates the probability of a farm borrowing from FCS having a higher predicted probability than a farm borrowing from banks. Based on this statistic, the model correctly identified farms likely to borrow from FCS 61.8 percent of the time.

The estimations confirm earlier research that showed the FCS serves larger farming operations in the farm credit market. Full-time commercial size farmers were more likely to borrower from the FCS while the part-time and hobby farm segments of the farm credit market were more likely to be served by banks (table 4). The odds ratio indicates that full-time commercial-size farms are 1.678 times more likely than smaller size farms to be FCS borrowers (table 5). Meanwhile part-time and hobby farms were twice as likely to borrow from banks than full-time farms. While the parameter estimates for family farms was not as expected, the odds ratios suggest little effect, with family-size farms being only 1.04 times more likely than other size groups to borrow from banks.

Local credit market conditions were found to impact the likelihood of borrowing from FCS. A greater presence of farmers and agricultural banks combined with a stronger economy should result in more competitive farm credit markets and less demand for loans provided by FCS. Results indicated that farm borrowers in regions characterized by fewer agricultural banks, lower incomes, and fewer farmers were more likely to borrow from FCS. Farmers located in counties with access to a FCS branch, but no agricultural banks were 1.14 times as likely to borrow from the GSE. Farmers in low-income counties were 1.41 times more likely than farmers in higher income counties to borrow from FCS. The negative sign for variable measuring the ratio of farm residents to total residents indicates that farmers in counties with a greater presence of farmers are more likely to borrow from banks.

The model results indicate that borrowers which were more solvent, less financially stressed, more profitable, and had greater debt service capacity were more likely to be FCS customers. This more conservative lending policy is consistent with that of a single sector lender and with the regulatory environment in which it operates. Some of these results, however, may be a result of FCS's greater role in serving full-time commercial farmers and banks' stronger role in the part-time and hobby farm market. Part-time and hobby farms are likely to have be less efficient and profitable, not considering the effect of nonfarm income. The financial stress and term-debt-coverage ratios, however, included nonfarm income. Thus, the significance of these two variables is consistent with the FCS's greater lending to lower risk segments of the farm credit market.

A financially vulnerable farm was only 0.795 times more likely than farms more financially secure to be a FCS borrower compared to other farms. Greater levels of indebtedness, as measured using the debt-to-asset ratio, increased the probability of a farm borrowing from banks. A one-percent increase in the adjusted debt-to-asset ratio decreased the probability of borrowing from FCS by 0.10 percent[8]. Farms with greater term-debt-coverage ratios were more likely to borrow from FCS. However, changes in the term-debt-coverage ratio had a slight impact on the probability of being a FCS borrower. A one-percent increase in the term-debt-coverage ratio improved the probability of being a FCS borrower by only 0.06 percent.

The odds ratio indicates that a young or beginning farmer is1.392 times more likely to be a FCS borrower. Likewise, farmers over the age of 55 were only 0.912 times as likely as farmers under the age of 55 to be a FCS borrower, which is consistent with the expectation that older farmers in the farm credit market demand financial services available from commercial banks.

The results for the presences of racial and ethnic minorities in a county suggest that the likelihood of being a FCS borrower rose as the presence of minorities fell. For every 1-percent rise in the share of farm residents who are members of a racial or ethnic minority group, the probability of being a FCS borrower falls by 0.083 percent suggesting an inelastic relationship between minorities and FCS lending. Racial and ethnic minorities are geographically concentrated, with many large regions having few racial or ethnic minorities present. Further analysis compared counties where the presence of racial and ethnic minorities is greater than the national average with all other counties. It was found that among counties with a greater presence of racial and ethnic minorities, farms were only 0.6 times as likely to be a FCS borrower compared to banks

Summary

In general, model estimation results are consistent with the expectation that the Farm Credit System and commercial banks serve somewhat different segments of the farm credit market. As anticipated 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 that focus FCS lending on "full credit to full-time bona fide farmers" and "conservative credit to part-time farmers."

This finding is also consistent with the expectation that larger full-time farmers benefit economically more from the specialized farm financial services provided by the FCS and therefore, are more likely to choose the GSE relative to banks. Overall, the FCS may be more competitive on loans to larger farms, while banks, with their broader array of financial services, are more likely to be more competitive with smaller farms. Even with its funding advantages it may be more difficult for the FCS to recoup fixed lending costs and remain competitive with full-service banks when credit requests are small.

Estimation results are consistent with past research that has shown FCS serves more creditworthy segments of the farm credit market. FCS customers were less heavily indebted, more profitable, and had greater debt repayment capacities. Because the FCS's lending is concentrated in agriculture its managers and its regulators would be expected to more risk adverse relative to commercial banks. Results from earlier studies also had suggested that FCS borrowers were more highly capitalized when compared bank customers. However, this research suggests this finding is

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[8] Log-odds ratios are for continuous variables are estimated based on a one-unit change in the independent variable. This results in the magnitude of the log-odds ratio being affected by the units chosen to measure the dependent variable. Therefore, sensitivity of results for continuous variables are shown using elasticity as the percent change in the dependent variable as a result of a 1 percent change in the independent variable.

largely a function of farm size. When borrower net worth was normalized by the value of the farm's production, there was no difference in capitalization levels between FCS and bank borrowers.

Results also indicate that farms in counties with fewer agricultural banks, or fewer farmers, and or experiencing greater economic distress were more likely to turn to FCS lenders for their credit needs. This is consistent with FCS's statutory requirement that it serve all bona fide farmers with a basis for credit, regardless of location. It may also suggest that FCS lenders are serving as a source of credit in those areas where farm credit markets may be less competitive.

In contrast to the results from earlier studies, the FCS was found to be a more likely supplier of credit to young and beginning farmers than commercial banks. An increase in lending to this segment of the farm credit market might be the result of Farm Credit Administration policy initiatives undertaken since 1998 that were designed to bolster FCS lending to these farmers. Finally, farmers in counties with a significant racial and ethnic minority population were less likely to borrow from FCS. This result was inconsistent with the expectation that the FCS fills voids in credit markets. One possible explanation for the inconsistency might be the fact that racial and ethnic minority farmers tend to operate small and part-time farms that the GSE is not always competitive in serving.

Table 2. Financial and structural characteristics of farms acquiring debt in 2001 and 2002, by lender group providing majority of new credit.				
	By Primary Lender of New Debts			
	Banks	FCS	All other lenders	All farms W/ new loans
Number of farms acquiring debt	184,000	30,700	77,000	291,700
	Dollars per farm			
Farm assets	661,909	955,384	576,167	670,418
Farm debt	173,554	219,040	122,805	165,019
New debt	106,781	132,644	42,057	92,493
Commercial banks	100,570	D	D	63,886
Farm Credit System	D	123,691	D	13,334
Farm net worth	488,355	736,344	453,361	505,398
Net worth per $ of production	2,755	2,699	3,433	2,880
Value of farm production	177,258	272,799	132,053	175,480
Total household income	62,680	71,264	69,121	65,276
Farm inc. to household inc.	3,683	26,814	7,085	7,041
Acres operated	769	966	496	718
Financial ratios:	Percent			
Solvency				
Year-end Debt-to-Asset ratio	26.2	22.9	21.3	24.6
D/A w/repaid operating loans	26.5	23.4	21.7	24.9
Share financially stressed	5.8	5.4	4.5	5.4
Debt Capacity				
Term-debt-coverage ratio	75.9	97.2	141.8	89.3
Debt repayment capacity utilization	51.1	51.8	38.5	48.1
Profitability & efficiency				
Operating expense ratio	85.4	78.4	84.5	84.1
Return on farm assets	-0.2	1.1	-1.1	-0.3
Profit margin	-0.8	3.2	-4.6	-1.0
Primary operator age (years)	49.6	48.4	48.0	49.1
	Percent			
Over 55 years of age	28.5	24.2	24.0	26.9
Beginning or young farmers	9.9	13.0	9.4	10.1
Full-time	10.1	24.6	9.5	11.5
Family	8.9	12.5	8.3	9.2
Other commercial-size	10.2	14.3	8.0	10.0
Part-time	38.5	25.1	36.2	36.5
Hobby	32.4	23.5	38.0	32.9
Competitive factors:				
Farm residents/total in county	6.8	6.0	4.2	6.1
Share in low-income counties	17.7	19.7	11.1	16.2
No. of Ag. banks in the county	3.7	3.2	2.4	3.3
Racial/ethnic share of all farmers in cty	5.3	5.9	6.2	5.6

Source: 2001 and 2002 Agricultural Resource Management Survey. D – Insufficient data for disclosure.

Table 3. Multivariate logit model analyzing loans made by the FCS and banks in 2000 and 2001	
Summary statistic	Chi-square
Likelihood ratio (W/15 d.f.) Wald Score	17,512 *** 16,728 *** 17,746 ***
Association of Predicted Probabilities and Observed Responses	
	Percent
Concordant	61.0
Discordant	38.4
Tied	0.6
C	.61.8

Table 4. Regression coefficients and asymptotic t-values from logit model analyzing loans made by FCS and banks in 2000 and 2001

Parameter	Estimate and Standard error \ 1
Constant	-1.0201 (0.0163)
FULLTIME	0.5177 (0.0159)
FAMFARM	-0.0462 (0.0178)
PARTTIME	-0.8509 (0.0156)
HOBBY	-0.6529 (0.0161)
COMPETITION	0.1301 (0.0110)
FARM-SHR	-0.0362 (0.0009)
MED_HHI	0.3433 (0.0124)
DA RATIO	-0.4486 (0.0218)
VULNERABLE	-0.2295 (0.0220)
TDBTCOV	0.0074 (0.0004)
PMARGIN	0.3431 (0.0298)
CAPITAL	-1.1493 (0.0671)
OVER_55	-0.0925 (0.0111)
BEG_YOUNG	0.3306 (0.0150)
RACE_ETHNIC	-0.0156 (0.0006)

1/ All estimates significant at 0.0001 level of significance or greater.

Table 5. Sensitivity of predicted probabilities to changes in parameter values.	
Variable	Odds ratio \1
FULLTIME	1.678
FARMFARM	0.955
PARTTIME	0.427
HOBBY	0.521
COMPETITION	1.139
MED_HHI	1.410
VULNERABLE	0.795
BEG_YOUNG	0.912
OVER_55	1.392
	Elasticity \2
DA RATIO	-0.098
FARM-SHR	-0.185
TDBTCOV	0.006
PMARGIN \ 3	0.283
CAPITAL	0.000
RACE_ETHNIC	-0.083

\1 Change in probability of farmer being included in FCS market segment as a result of independent variable having a value of 1.
\ 2 Percentage change in probability of farmer being included in FCS market segment as a result of a 1 percent change in the independent variable.
\ 3 Since the mean ROA was approximately equal to 1, the elasticity was evaluated at 1 percent.

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The DuPont Profitability Analysis Model: An E-Learning Application and Evaluation

Jon Melvin, Michael Boehlje, Craig Dobbins and Allan Gray*

Abstract

Successful farm business managers must understand the determinants of profitability and have an overall long-term or strategic management focus. The objective of this research is to help producers understand the impacts of different production, pricing, cost control and investment decisions on their farms financial performance. This objective will be accomplished by developing and testing a computer-based training and application tool to facilitate determining the financial health of farm businesses using the DuPont profitability analysis model. The results of the two experiments indicate that the computer software was effective for teaching techniques of profitability analysis contained within the DuPont model.

Keywords: DuPont profitability analysis, e-learning, computer assisted analysis, return on equity (ROE), return on assets (ROA)

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Introduction

It is generally perceived that financial management is important as a management function of any business, including farm businesses. Poor financial practices rank second only to economic conditions as a cause of business failure, according to Dun & Bradstreet (1994). A study by Gaskill, Van Auken, and Manning (1993) examined causes of business failure in the apparel industry; they found that poor financial control is a main cause of business failure. Wichman (1983) reported that accounting capacity was an important aspect in determining small business success or failure. Lauzen (1985) characterizes the first 5 years of a business as being the critical time period. He argues that by analyzing financial statements and developing good managerial skills, a business owner can increase his chances of success. Wood (1989) specifically cites the importance of financial education and training as a determinant of whether a business will succeed.

Boehlje et al. (1999) recognize the importance for farm business managers to evaluate and monitor financial performance. They also indicate that financial management is important because of the link between managerial decisions and rates of return. They argue that the farm manager must collect accurate data for a financial evaluation and then make the appropriate adjustments if necessary. Firer (1999) agrees stating that managers need to have at least a basic understanding of how to determine the financial health of their business and the financial implications of different strategies. Plumley and Hornbaker (1991) argue that the economic environment encountered by the farm sector places much importance on finance in farm management. Mumey (1987) also argues that if concentration on farm production has proved successful to farm performance, then increased concentration on financial management might also be justified.

Profitability Analysis

Profitability analysis and assessment of the fundamental drivers of profitability is a critical component of evaluating financial performance. Performance measures like the operating profit margin, asset turnover ratio, return on assets and return on equity -- and more importantly how they are impacted by marketing, operations, investment and financing decisions -- are extremely valuable to a farm manager. The operating profit margin shows the amount that each dollar of sales yields to net income. The asset turnover rate measures the revenues generated per dollar of assets and indicates how efficiently the business uses its assets. The return on assets is a measure that managers can use to determine if capital is generating an acceptable rate of return. Return on equity helps managers determine whether or not the debt of the farm business is working for or against them. Together these measures help to show how well the farm business is performing financially. These four measures are core to the manager's analysis of business financial performance and are neatly summarized in the DuPont profitability analysis model.

The DuPont Model

The DuPont model is a common and useful way to assess and understand the drivers of profitability (Barry, 2000: p.121). The DuPont model is a ratio-based analysis that allows managers to see the interactions among the important variables in the cost-volume-profit chain (Van Voorhis, 1981). Blumenthal (1998) argues that the DuPont model is a useful way of visualizing financial information and is a good tool for getting people started in understanding how managerial decisions have an impact on financial performance.

Firer (1999) explains the DuPont model as a financial analysis and planning tool intended to develop an understanding of the factors that affect the return on equity (ROE) of the firm using straightforward accounting relationships. He argues that the DuPont model allows for the assessment of the components of ROE and assists management in examining the possible influence of strategic initiatives on financial performance. Ross et al. (1999) further identify three factors that impact the ROE as it is represented in the DuPont model. The three factors are: (1) operating efficiency (measured by profit margin); (2) asset use efficiency (measured by asset turnover); and (3) financial leverage (measured by the equity multiplier). Eisemann (1997) agrees saying that the ratios that establish ROE reflect three major performance characteristics: one income statement management feature (profit generated per sales dollar) and two balance sheet management features (sales generated per asset and the amount of solvency risk).

Application to Farm Businesses

As noted earlier, a producer needs to go beyond production management and address two fundamental concerns: (1) "How am I doing from a financial perspective?" and (2) "How can I do it better". Adages such as "lower costs" or "produce more" have often been taken as a point of fact. It is simply assumed that pursuing management strategies like these will automatically improve financial performance. An analysis usually is not done to determine which strategies warrant the most attention. The DuPont model allows producers to analyze the potential for improved performance by concentrating on variables that have the most bearing on that performance.

A very important measure of financial success to any business, farm or otherwise, is the return on equity (ROE). Assuming a producer has an income statement to obtain net income and a balance sheet to obtain owner equity, the ROE is an easy metric to calculate using the simple formula of net income divided by owner equity. However, viewing the ratio separately rather than in combination with other metrics does little to inform management on how to improve performance (Van Voorhis, 1981). If ROE is found to be less than return on assets (ROA) or has declined recently, the DuPont model suggests two basic approaches to improve performance. Analysis can be done to determine whether the ROE can be improved through the income stream or the investment stream (Figure 1).

Initially most producers may be concerned more with the income stream than the investment stream, because the production decisions made in the farm business will usually have a more direct effect on the variables in the income stream. The income stream involves variables such as selling price, expenses, net sales, profit margin, and the use of assets. If the producer discovers a major weakness in the ROE, backtracking through the income stream and determining where changes can be made will easily identify one set of potential reasons for the weakness.

For example, if the producer discovers that ROA is not satisfactory, he can track this back to asset turnover and net profit margin. The analysis can be further tracked to net sales and total cost if the net profit margin is determined to be the main reason for the low ROA. Net sales could be improved by increasing the price received (better marketing) or by increasing the volume of product sold (increasing yields or productivity). A farmer will most likely consider these actions, but the DuPont model offers an opportunity to do comparative statics and determine what options will most benefit the producer.

The second approach to improving ROE, through the investment stream, culminates in the financial leverage multiplier. Most of the backtracking through the investment stream will follow total assets. From basic accounting we know that total assets are equal to total liabilities plus owner equity. This simply means that all assets are either claimed by creditors or owners and this allows us to break the investment stream into two more sections, total debt and owner equity.

It is important for a producer to understand what changes occur in ROE as liabilities, equity and assets are restructured. For example, a producer might hypothesize that by decreasing his debt load he will increase his profitability because the interest expense of the business will decrease. However, by analyzing the investment stream of the DuPont model the producer will realize that if this reduced debt load requires an increase in owner equity to maintain the asset base of the business, the financial leverage multiplier will decline and the ROE may also decline. Again, by doing simple comparative statics the producer will see the consequences of different financing decisions.

DuPont Model Software

To help farm producers better understand the impacts of different production, pricing, cost control and investment decisions on financial performance, a computer-based financial analysis training and application tool was developed to facilitate analyzing the financial health of farm businesses. The software analysis tool was intended to introduce the DuPont profitability analysis in a user-friendly setting with audio help and instruction. The computer software was created using Microsoft Visual Basic 6.0[1] and packaged as a stand-alone program. Thus the program can be used without the assistance of an additional Microsoft application such as Excel. The computer software is segmented into two main sections: a tutorial and an analysis application.

The tutorial was developed to familiarize the user with the DuPont financial analysis model as well as how to operate the software. The tutorial begins by explaining the general organization and concepts of the DuPont model. Once this is complete, the tutorial continues by describing the formulas used to perform the profitability analysis and provides a corresponding flow chart to better visualize the calculations. The tutorial finishes by illustrating how to complete the DuPont analysis with an example farm business.

The analysis application was developed to enable the user to evaluate the profitability of their farm business. The analysis portion of the DuPont software allows the farm manager to look at areas for improvement and do preliminary long-run planning. The analysis section is divided into three levels. The Level I analysis only requires data on gross revenue, fixed expense, variable expense, interest expense, total assets and total equity (Figure 2, Panel A) to perform the DuPont analysis and is the most straightforward of the three levels of analysis. The results of the analysis are summarized as return on equity (ROE), return on assets (ROA), operating profit margin (OPM) and asset turnover ratio (ATR) as illustrated in Panel B of Figure 2. The Level I analysis follows the typical structure of the DuPont analysis described by most finance text books and publications.

The Level II analysis requires more detailed information; for each enterprise or business unit, average price, volume per unit, total units and variable cost per unit must be entered (Figure 3). Up to five enterprise classifications can be entered in the Level II analysis. The Level II

[1] Microsoft Visual Basic 6.0 is a registered trademark of Microsoft Corp. 1987-2000

analysis was designed to help the farm producers using the software with the diagnostics of specific pricing, cost control, enterprise choice, productivity, etc. decisions to improve. profitability.

The Level III analysis allows for two long-run changes to be made to the farm business: an expansion analysis and a contraction analysis (Figure 4). Level III uses the base information entered for Level II to initiate the analysis. This means that the Level III analysis can be conducted only after the Level II analysis has been completed. The Level III analysis was intended to assist the farm producer with strategic positioning decisions related to growth or downsizing the business as well as different business ventures such as contract production or custom farming.

Audio instruction and help sections are also included in the computer software. Audio instruction is included throughout the tutorial and the analysis to provide guidance and instruction in the use of the computer program and interpretation of the results.

Software Test

An experiment was conducted to test the differences in knowledge and understanding of profitability analysis prior to and after use of the computer assisted educational program. Two sample groups were used: Purdue graduate students and farm producers. The two groups were tested separately; however, the same experiment was applied to both groups.

For the experiment, each participant was given initial instructions by the administrator and an instructional sheet. The instructions for the experiment were as follows: 1) Take Test #1; 2) Go through the tutorial; 3) Go through the analysis using the provided case study; 4) Take Test #2. These instructions were meant to guide the test participant through the experiment. The approximate time to complete the experiment was about 1 hour.

Test #1 and Test #2 were identical and consisted of 10 multiple choice questions based on ideas and principles of financial analysis that are components of the DuPont profitability analysis model. The questions were categorized into three areas of learning: 1) calculation procedures of the DuPont model, 2) financial concepts contained in the DuPont model, and 3) application of financial concepts to managerial decisions. Calculation based questions were included to determine how well the participants learned the mechanical and operational details included in the DuPont model. Application based questions were included to help determine how well the participants were able to combine calculation and conceptual questions to help solve real life problems. Conceptual based questions were included to evaluate the participant's ability to comprehend fundamental financial concepts that are embodied in any business.

Summary Results

Graduate Students

A random sample of 20 Purdue University Agricultural Economics graduate students was used for the first experimental group. To obtain the sample, an e-mail was sent to all graduate students within the Department of Agricultural Economics asking individuals interested in participating in the experiment to respond. None of the graduate student subjects were pre-selected and their knowledge of financial concepts was unknown to the experiment administrator.

Table 1 contains the results from the graduate student group. Test #1 and Test #2 are the respective test scores for participants before and after the use of the computer program. Other information gathered includes: educational level, academic area, rating of knowledge of financial concepts, rating of computer skills, and previous participation in an experiment of this nature. Self-assessment of financial concepts and computer skills were based on a scale of 1 to 5, with 1 being poor and 5 being excellent.

There were fourteen MS and six PhD students that participated in the experiment. Different academic areas included: agribusiness, international development, agricultural marketing, and agricultural finance. None of the graduate student participants indicated that they had ever participated in a study of this nature. The average self-assessment rating of knowledge of financial concepts before the experiment was 2.25 and the average self-assessment rating of computer proficiency was a 3.85 (Table 1).

The results of the graduate student tests are summarized in Table 1. The averages are the average score of all the participants out of 10 points. Overall the scores increased for the graduate students, after using the software; 17 of the 20 graduate students increased their score from the first test to the second. The average score for the first test was a 4.25 and the standard deviation was 1.74. The average score for the second test was 6.65 and the standard deviation was 1.79. The minimum score on Test #1 was a 0 and the maximum score was a 7. The minimum score on Test #2 was a 3 and the maximum score was a 10.

The average test scores for the three areas of learning also increased from the pre-test to the post-test (Table 1). The average score for the calculation based questions on the pre-test was 1.3 and the average score for the post-test was 2.35 out of three questions. The average score for the application questions was 0.8 on the first test and 1.85 on the second test out of three questions. The final area of learning, conceptual, exhibited an average first test score of 2.15 and an average second test score of 2.50 out of three questions.

Overall the calculation and application questions exhibited a larger number of test participants increasing their score from the pre-test to the post-test than the conceptual questions. The calculation questions had 15 people increase their score and the application questions had 14 people increase their scores from the first test to the second. However, the initial scores for the conceptual based questions was over a full point higher than the average score for the application based questions and was almost a full point higher than the average score for the calculation questions. The conceptual based questions also had the highest post-test average (2.5/3) of the three areas of learning.

Farm Producers

A random sample of 20 farm producers was used for the second experimental group. None of the farm producer test subjects were pre-selected and their knowledge of financial concepts was unknown to the experiment administrator. Participants for the farm producer group were recruited through ag extension educators and through leads provided by faculty and students in the Department of Agricultural Economics at Purdue University. Participants for the farm producer group came from Indiana, Tennessee, and North Dakota. Each participant was given initial instructions by the test administrator to follow the instructional sheet provided on the front of the test packet.

Table 2 contains the results from the farm producer group. Different academic areas of the farm producers included agribusiness, accounting and ag science (Table 2). None of the farm producer participants indicated that they had ever participated in a study of this nature. The average self-assessment rating of financial concepts before the experiment was 2.37 and the average self-assessment rating of computer proficiency was 3.11 (Table 2).

Overall the scores increased for the farm producers, with 13 of the 20 farm producers increasing their score from the first test to the second and 2 of the participants exhibiting a lower score on the second test. The average score for the first test was a 3.68 and the standard deviation was 1.95. The average score for the second test was 5.21 and the standard deviation was 1.05. The minimum score on Test #1 was a 0 and the maximum score was an 8. The minimum score on Test #2 was a 2 and the maximum score was a 9.

The average test scores for the three areas of learning also increased from the pre-test to the post-test (Table 4). The average score for the calculation based questions on the pre-test was 1.50 and the average score for the post-test was 2.20. The average score for the application questions was 0.45 on the first test and 1.00 on the second test. The final area of learning, conceptual, exhibited an average first test score of 1.80 and an average second test score of 1.95. The calculation questions had 13 people increase their score from the first test to the second. The application and conceptual questions had 8 people increase their scores from the first test to the second.

Sign Test

The graduate student and farm producer test results were examined to determine if the increase in test scores from Test #1 to Test #2 are statistically significant. To test for the differences in the paired data, a sign test was used. The sign test for the differences is a non-parametric method for determining if two columns of observations are significantly different from one another (Siegel, 2003). The sign test requires that the data set is a random sample from the population of interest and is a two-tailed test. To determine whether or not the two samples are significantly different, the sign test uses a ranking system based on a modified sample of the data. The ranks for the sign test are included in Table 3.

The procedure for the sign test is as follows[2]:

1) Find the modified sample size, m, by calculating the sum of data values that change between the first and second columns.

2) Establish the limits for m.

3) Count the data values that went up and compare to the limit.

4) If this count falls outside the limits, then the two samples are significantly different. If the count falls within the limit, the two samples are not significantly different.

[2] Andrew Siegel, “Practical Business Statistics” McGraw-Hill (2003)

Sign Test – Graduate Students

The graduate student group contained 20 participants; however the number of data values that went either up or down is 18, thus the modified sample size is 18. It should be noted that it does not matter if a test score decreased from the first test to the second when determining the modified sample size. Because absolute values are assigned, it only matters that the scores are different. The limits for testing at the 10% level at a modified sample size of 18 are 4.9 and 12.1, as shown in Table 3. The graduate student group had 17 participants with higher test scores on the second compared to the first test, which indicates that there is a statistically significant difference between the test scores. Thus the computer program was statistically significantly helpful in improving the participants understanding of profitability analysis.

Sign tests were also conducted on the respective categories of questions (calculation based, conceptual based, and application based) to determine if there are differences in these areas of learning. The modified sample size for the calculation based questions is 18 and the limit for this sample size at the 10% level is therefore 5 and 13. The number of test scores that increased from the first test to the second for the calculation based questions is 15. Thus, there is a statistically significant increase from Test #1 to Test #2 in the calculation based questions.

The modified sample size for the application based questions was 16 and the limit for this sample size at the 10% level is therefore 4.5 and 11.5. The number of test scores that increased from the first test to the second for the application based questions is 14. Thus, there is a statistically significant increase from Test #1 to Test #2 in the application based questions.

The modified sample size for the conceptual based questions was 11 and the limit for this sample size at the 10% level is therefore 2.5 and 8.5. The number of test scores that increased from the first test to the second for the conceptual based questions is 8. Thus, the increase from Test #1 to Test #2 in the conceptual based questions is not significant. However, it should be noted that the number of participants that increased their scores is close to the upper limit of 8.5.

Sign Test – Farm Producers

The farm producer tests were also examined to determine if the increase in test scores from Test #1 to Test #2 are significant. The farm producer group contained 20 participants; however the number of data values that went either up or down is 15, thus the modified sample size is 15. The limits for testing at the 10% level at a modified sample size of 15 are 4.1 and 10.9, as shown in Table 3. The farm producer group had 13 participants with higher test scores on the second compared to the first test, which indicates that there is a statistically significant difference between the scores on the two tests for this group.

Sign tests were also conducted on the respective categories of questions (calculation based, conceptual based, and application based) for the farm producers. The modified sample size for the calculation based questions is 15 and the limit for this sample size at the 10% level is therefore 4.1 and 10.9. The number of test scores that increased from the first test to the second for the calculation based questions is 13. Thus, there is a statistically significant increase from Test #1 to Test #2 in the calculation based questions.

The modified sample size for the application based questions is 10 and the limit for this sample size at the 10% level is therefore 2.1 and 7.9. The number of test scores that increased from the first test to the second for the application based questions is 8. Thus, there is a statistically significant increase from Test #1 to Test #2 in the application based questions. The modified sample size for the conceptual based questions is 12 and the limit for this sample size at the 10% level is therefore 2.9 and 9.1. The number of test scores that increased from the first test to the second for the conceptual based questions was 9. Thus, the increase from Test #1 to Test #2 in the conceptual based questions is not statistically significant. However, it should be noted that the number of participants that increased their scores is close to the upper limit of 9.1.

Conclusions

The modern farm business manager must function in the critically important role of general manager, understand the determinants of profitability and have an overall long-term and strategic management focus. The objective of this research was to help producers understand the impacts of the different production, pricing, cost control and investment decisions on their farms financial performance. This objective is accomplished by developing a computer-based financial analysis training and application tool to facilitate determining the financial health of farm businesses. The tool was based on the DuPont Financial Analysis Model for assessing determinants of profitability and financial performance. The computer software is structured into two main sections: a tutorial and an analysis application. The tutorial was developed to familiarize users with the DuPont model as well as how to operate the software.

The computer-based educational tool was tested in two pre-test/post-test experiments; one with 20 graduate students and one with 20 farm producers. The financial test used for the experiments consisted of 10 multiple choice questions divided into 3 areas of learning: application, calculation, and conceptual. The results of the two experiments indicate that the computer software was effective for teaching techniques of profitability analysis contained within the DuPont profitability analysis model. Analysis of the graduate student group and the farm producer group indicates that the improvement associated with the overall test scores is statistically significant. Analysis of the categories of questions indicate that both the graduate student group and the producer group had a statistically significant improvement in test scores for the calculation and application based questions, but did not have significant improvements in test scores for conceptual based questions.

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Figure 1. DuPont Financial Analysis Model (Van Voorhis)

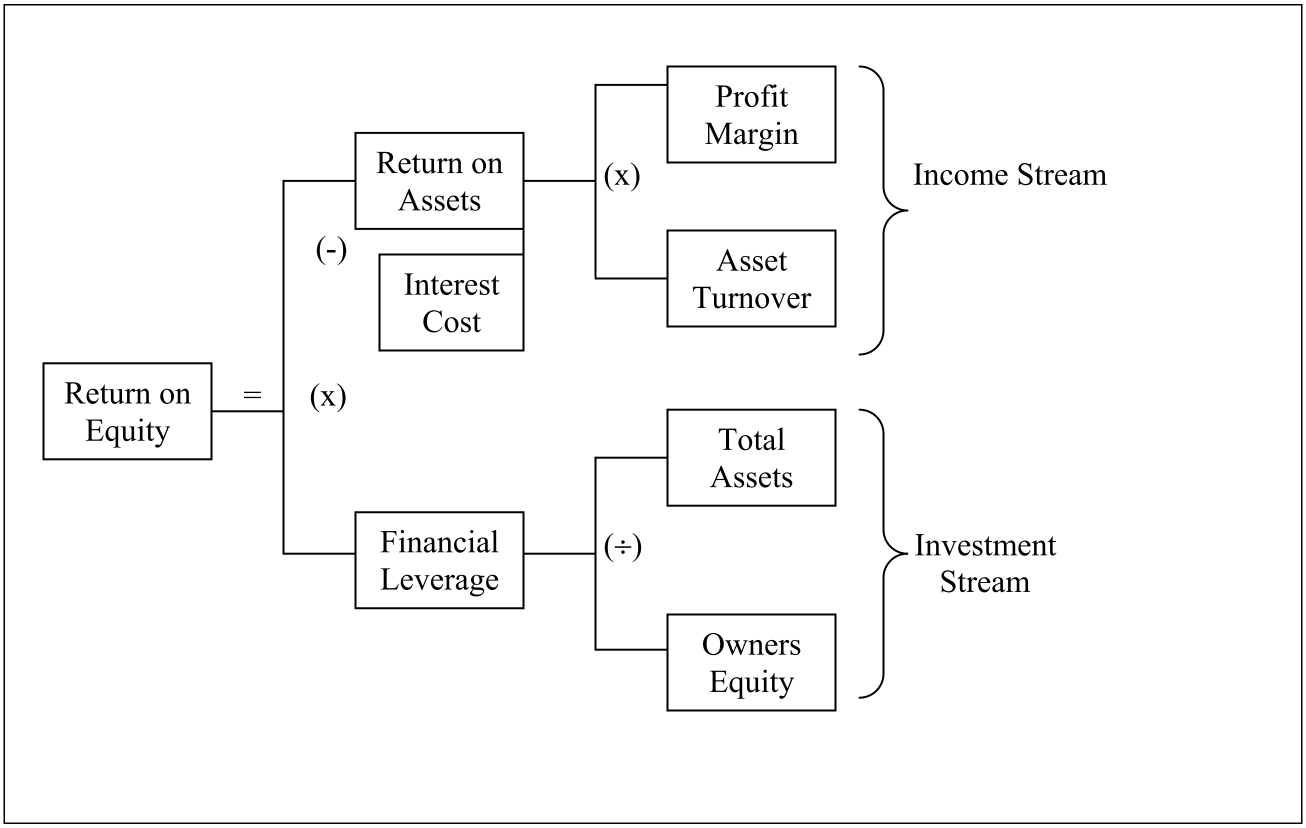
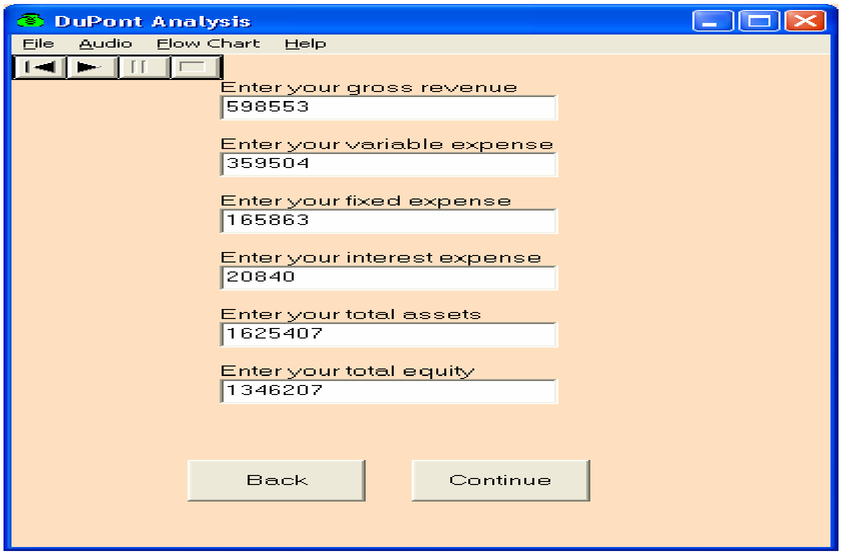


Figure 2. Level I DuPont Analysis Software Screenshots

Panel A. Input Data



Panel B. Analysis Results

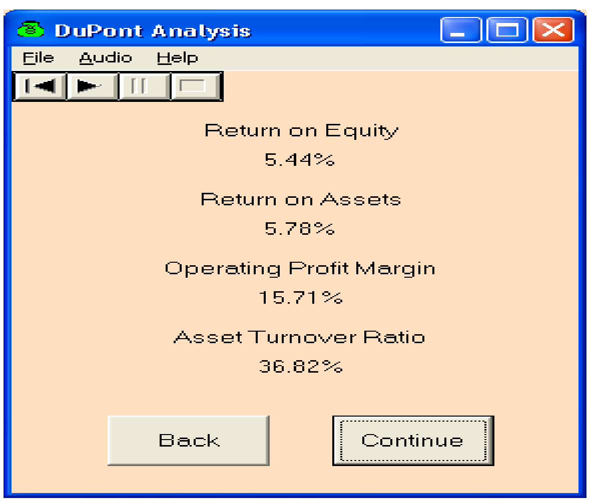
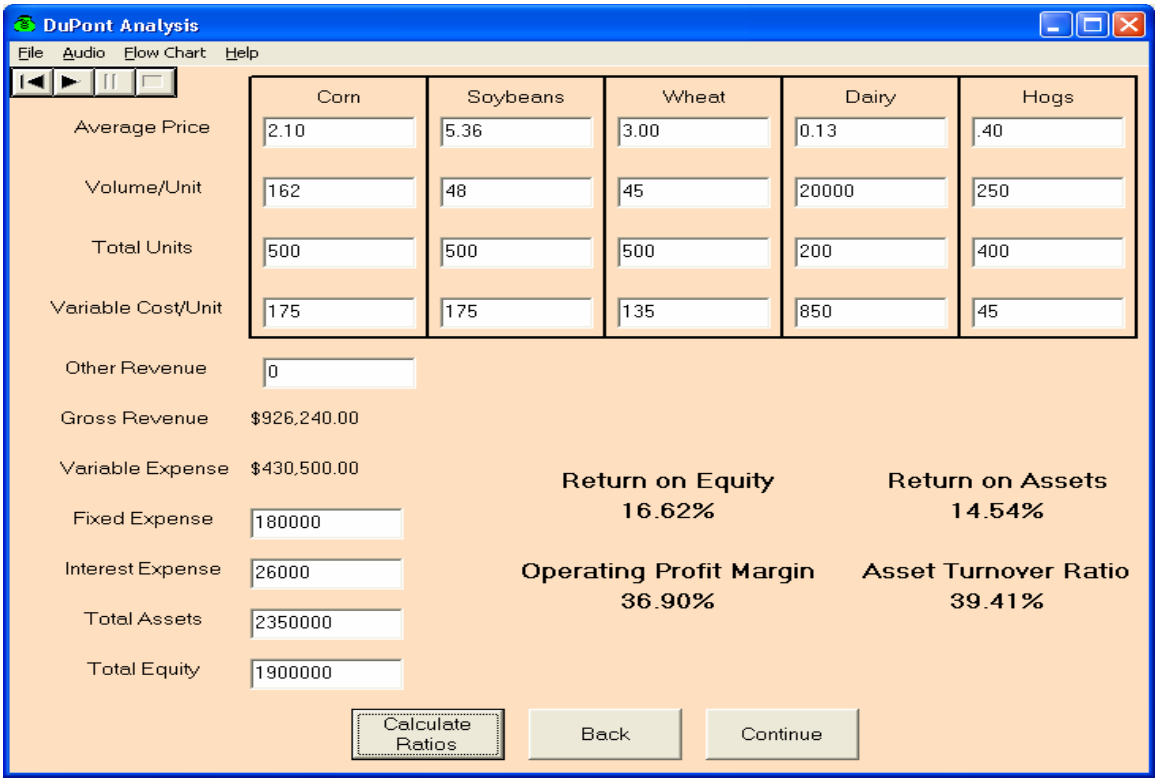


Figure 3. Level II DuPont Analysis Software Screenshots

Panel A. Input Data



Panel B. Analysis Results

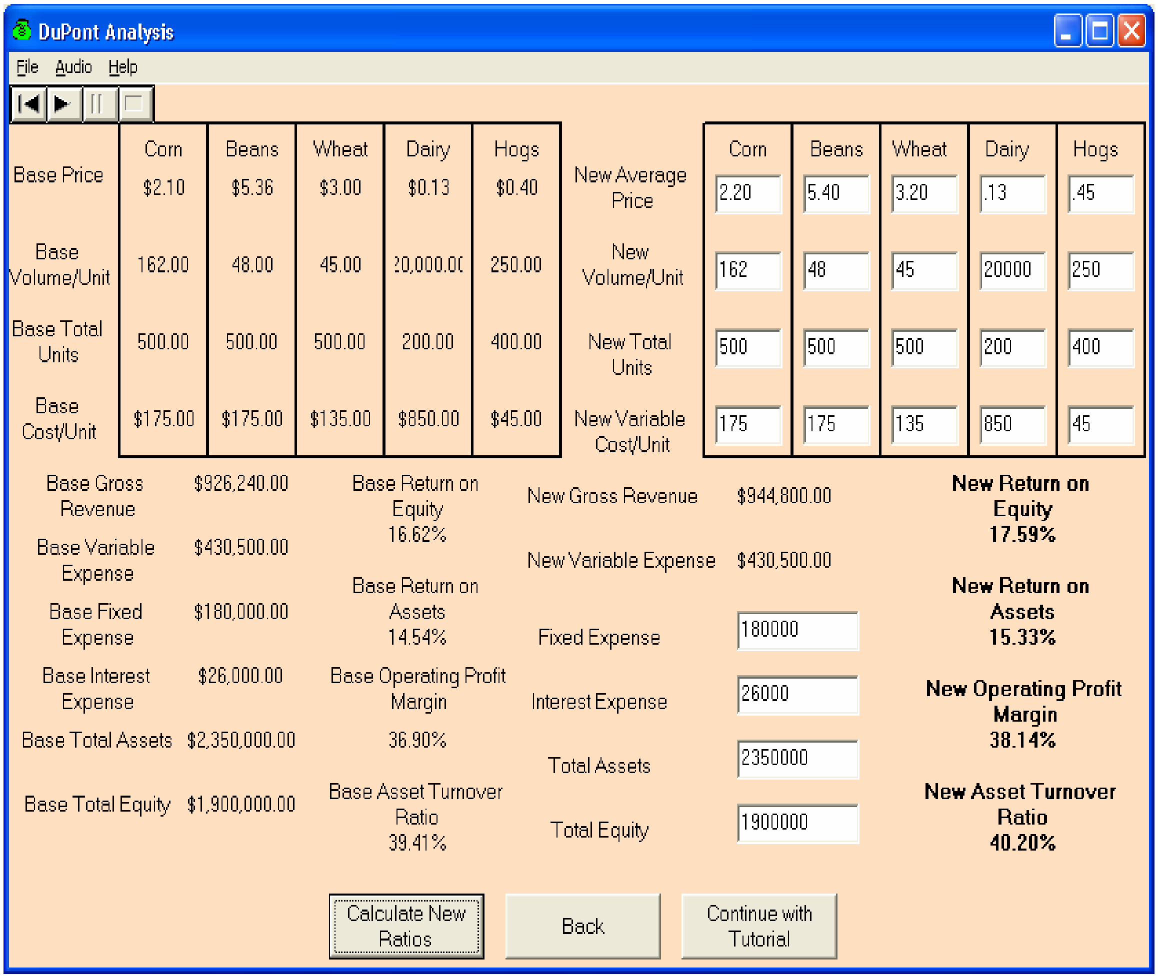
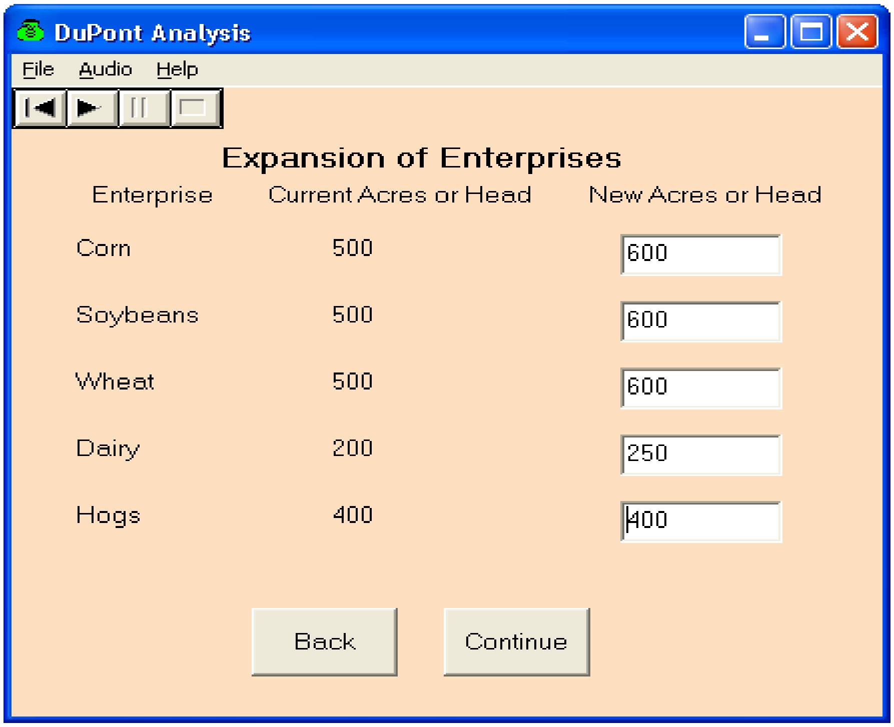
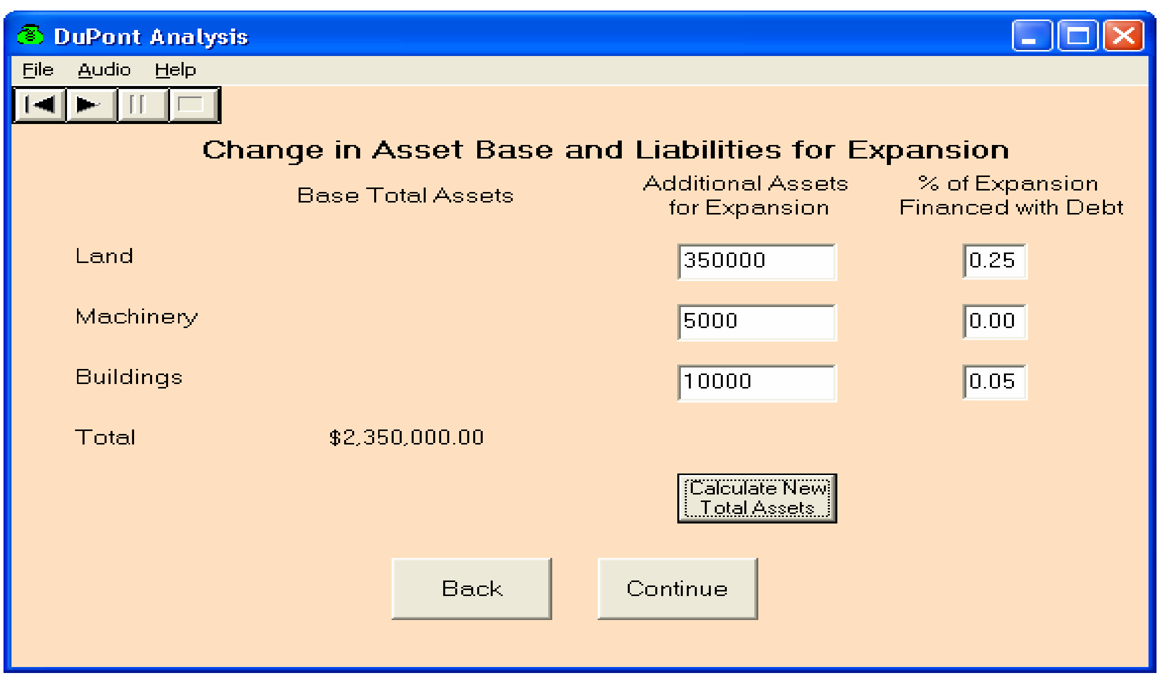


Figure 4. Level III DuPont Analysis Software Screenshot.

Panel A Input Data





Panel B. Analysis Results

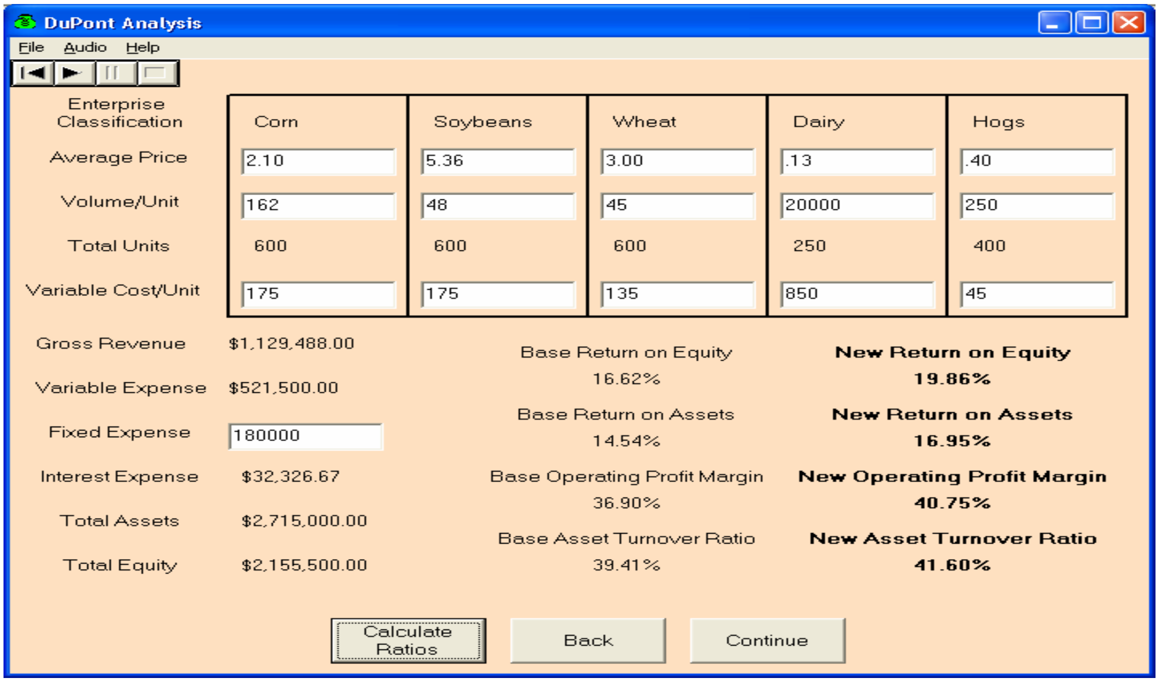


Table 1. Results from Graduate Student Group

	Overall		Calculation		Application		Conceptual		Concepts	Computer
	Test #1	Test #2	Test #1	Test #2	Test #1	Test #2	Test #1	Test #2		
Average	4.25	6.65	1.30	2.35	0.80	1.85	2.15	2.50	2.25	3.85
Std Dev.	1.74	1.79	0.92	0.93	0.77	1.23	0.93	0.83	1.07	0.59
Min	0	3	0	0	0	0	0	0	1	3
Max	7	10	3	3	2	4	3	3	4	5
Median	4	6	1	3	1	2	2	3	2	4
Increases	17		15		14		8			

Table 2. Results from the Farm Producer Group

	Overall		Calculation		Application		Conceptual		Concepts	Computer
	Test #1	Test #2	Test #1	Test #2	Test #1	Test #2	Test #1	Test #2		
Average	3.68	5.21	1.50	2.20	0.45	1.00	1.80	1.95	2.37	3.11
Std Dev.	1.95	2.02	0.89	0.83	0.60	1.08	1.06	0.83	1.12	1.05
Min	0	2	0	0	0	0	0	0	1	1
Max	8	9	3	3	2	3	3	3	4	5
Median	4	5	2	2	0	1	2	2	2	3
Increases	13		13		8		8			

Table 3. Ranks for the Sign Test*

	10% Test Level: Sign Test is Significant if Number is Either:		
Modified Sample Size, m	Less than	or	More than
6	0.5		5.5
7	0.9		6.1
8	1.3		6.7
9	1.7		7.3
10	2.1		7.9
11	2.5		8.5
12	2.9		9.1
13	3.3		9.7
14	3.7		10.3
15	4.1		10.9
16	4.5		11.5
17	4.9		12.1
18	5.3		12.7
19	5.7		13.3
20	6.1		13.9

*Adapted from Andrew Siegel, "Practical Business Statistics" McGraw-Hill (2003)

Sustainable Growth Trends in U. S. Agriculture

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Sustainable Growth Trends in U. S. Agriculture

Sustainable growth, measured by the sustainable growth rate, represents the maximum rate at which a firm can expand its sales without depleting its financial resources (Higgins 2001). If a firm grows at a rate greater than its sustainable growth rate then it must source capital from other sources, such as increased borrowing or the sale of assets. When growth in sales falls short of the sustainable growth rate, assets are being underutilized and cash will generally be accumulated in unproductive ways.

Financial leverage in agriculture has been of considerable interest to a wide range of stakeholders for over 20 years. The financial crises of the late 1980's and market instability in the late 1990's has exemplified the need to continually investigate models that aid in understanding farm debt decisions. For many, the expected utility-mean-variance approach to modeling farm financial structure decisions has provided considerable insights into the financial leveraging process (Collins; Barry and Robison; Barry, Baker and Sanint). Studies that have investigated the relationship between reductions in business risk and increased financial leverage include Collins, and Escalante and Barry who examine risk balancing in general; Turvey and Baker who examine relationships between leverage and hedging; Featherstone, et al. who examine various issues in agricultural finance and price support policies; Moss, Ford and Boggess who examine capital gains deductions; and Ahrendsen, Collender and Dixon who examine depreciation and investment tax credits.

Sustainable or balanced growth examines the same issue except from an operating and accounting point of view. It decomposes the returns to equity into four components; profit margin, retention (owner withdrawals), asset turnover and leverage. A decrease in any one of these ratios will lower the sustainable growth rate, and increase the likelihood that financial leverage will be required to sustain the farm. In contrast to the risk-balancing strategy derived in mean-variance models, the sustainable growth rate is proscriptive, as well as explanatory, and can provide insights into farm operating and financial decisions based on readily available accounting information. Furthermore, analyses of financial risk, as per the root model of Barry, Baker and Sanint, and Collins, take the variability of the return on assets or equity as given and do not ordinarily examine the operating factors that give rise to such volatility in the first place. The advantage of exploring a sustainable growth rate paradigm is that the paradigm possesses such insights. We are unaware of any previous studies that have explored the sustainable growth rate model in the context of agricultural finance, and we believe that this paradigm is a complement to previous studies.

The purpose of this paper is to first introduce the sustainable growth rate model as a conceptual paradigm and then to use the model to measure the sustainable growth rate in U.S. agriculture. A cross-sectional analysis is used so that all states and regions are covered. As a positivist approach to understanding financial leverage in agriculture, the use of sustainable growth in explaining debt is more than pragmatic. If sustainable growth rates fall relative to growth in sales, working capital shortfalls are inevitable. The model benefits the farm sector in three ways. First, from a business perspective, this inevitability principle provides a useful yet simple approach to explaining financial leverage and working capital strategies to farmers; Second, from a policy perspective, the inevitability principle provides some guidance as to how public policy can impact leverage decisions at the farm level; and third, from an academic perspective, this paper introduces as new, a tool that has been used by financial practitioners in the non-farm sector since the 1970's (e.g. Higgins 1972).

The next section describes the principles behind the sustainable growth model. This is followed by an analysis of sustainable growth in the U.S. farm sector. The results are then discussed and the paper is concluded.

The Sustainable Growth Model

The sustainable growth rate equation is given by

$$(1)\quad g_s = \left[\frac{NI}{R}\right]\left[\frac{NI - \mathrm{W}}{NI}\right]\left[\frac{R}{A}\right]\left[\frac{A}{E_{beg}}\right]$$

or

$$(2)\quad g_s = \left[\frac{NI}{R}\right]\left[\frac{NI - \mathrm{W}}{NI}\right]\left[\frac{R}{A}\right]\left[1 + \frac{\mathrm{D}}{E_{beg}}\right]$$

where NI is net income, R is revenue or sales, W is owner withdrawals, A is assets, D is debt and E_{beg} is the beginning of period equity. From left to right, the bracketed terms in the right hand sides of (1) and (2) represent the profit margin, retention ratio, asset turnover, and financial leverage, respectively. The relationship between sustainable growth and the return on equity (ROE) is given by the last term, which uses the beginning of period equity rather than the end of period equity. That is

$$(3)\quad ROE = \left[\frac{NI}{R}\right]\left[\frac{NI - \mathrm{W}}{NI}\right]\left[\frac{R}{A}\right]\left[1 + \frac{\mathrm{D}}{E}\right]$$

Assuming growth in equity is positive (i.e. $E_{beg} < E$), and all other things being equal, a comparison of (2) and (3) indicates that the sustainable growth rate is marginally higher than the ROE. Furthermore, all other things being equal, $E - E_{beg} > 0$ can only be attributed to increases in sales and if $E = E_{beg}$ then the change in sales will be zero. It is through this mechanism that the sustainable growth rate is linked to the percentage change in sales. The sustainable growth equation also includes as part of its product the return on assets (ROA). That is

$$(4)\quad ROA = \left[\frac{NI}{R}\right]\left[\frac{NI - \mathrm{W}}{NI}\right]\left[\frac{R}{A}\right]$$

indicating that the difference between the ROE and ROA is that the latter measures profitability on assets regardless of capital structure. To complete the relationships we can write

$$(5)\quad g_s = ROA\left[1 + \frac{\mathrm{D}}{E_{beg}}\right]$$

The sustainable growth relationships show how increases in sales must be managed. Balanced growth occurs when the percentage change in sales from one period to the next is equal to the sustainable growth rate. If this happens, then no adjustments need to be made to the profit margin, owner withdrawals, turnover or leverage. We refer to the difference between the growth in sales and the sustainable growth rate as the sustainable growth challenge (SGC). If sales increase faster than the sustainable growth rate, the SGC is positive and operating and financial adjustments need to be made in order to restore an accounting and operating balance. An increase in sales must be supported by any or all of the following: an increase in profitability (decrease in costs), a decrease in owner withdrawals, an increase in asset turnover, or an increase in financial leverage. In contrast, if the SGC is negative, sales growth is lower than the sustainable growth rate, cash surpluses increase and either sales must decrease, owner withdrawals increase, asset turnover decreases, or financial leverage is reduced.

The relationship between sustainable growth rates, operating leverage and financial leverage is depicted in Figure 1 with the growth in sales on the vertical axis and the ROA on the horizontal axis. Three balanced lines are presented for 0% debt, $D/E_{beg} = 0.25$ and $D/E_{beg} = 0.50$. Consider point A, which represents an unlevered farm with 6% ROA and sales growth of 6%. The strategic decision is to increase output and sales by 3% to 9%. Since 9% is higher than the sustainable growth rate of 6%, cash deficits will occur unless some actions are taken to bring sustainable growth into balance. If the decision is to maintain output and sales levels, unlevered actions will have to be taken to increase the ROA to 9% (at point B) as well. This can only be achieved by increasing the profit margin, decreasing withdrawals, or increasing the asset turnover ratio. If the asset base is relatively fixed in the short run then economies of scale must be achieved in order to ensure that the profit margin grows. Failing that, the growth can only be financed through minimization of owner withdrawals. But if growth in sales was achieved by expanding the asset base then the asset turnover ratio could in fact decrease, putting even greater pressure on the profit margin and retention ratio as means to manage growth. For most farmers in competitive markets this would be difficult. Point C in figure 1 shows an alternative strategy. Holding the ROA constant, the increased sales can be balanced by increasing debt to 50% of beginning equity. In reality, increased growth will most likely be a combination of changes to ROA and financial leverage, e.g. point D in Figure 1 with an increase in debt to 25% of equity and an increase in the ROA from 6% to about 7.2%.

It has long been argued that the increase in farm size has been justified based on economies of scale which reduce costs on a per unit basis. If output increases at a lower per unit cost, the anticipated profit margin would increase. Holding all other factors constant, economies of scale can be used to justify a balanced growth strategy with increased sales. That is, if farm expansion coincides with increased sales (active growth) without achieving economies of scale (actual growth exceeds sustainable growth) then the balance can only be maintained by decreasing household consumption, increasing financial leverage, or increasing asset turnover. This latter consideration has also been the focus of considerable interest in the agricultural finance literature. If sales can increase without having to increase the asset base, even if profit margins remain constant, then increased sales growth can be balanced with sustainable growth.

The introduction of high yielding or genetically modified crops is an example of how such economies can emerge. However, if the asset base is increased through the acquisition of land or other capital, and inflated on speculative prices, then the sustainable growth rate can fall as the asset turnover declines. If increased profit margins are not sufficient to offset lower asset turnover, then the growth in sales will exceed the sustainable growth rate. Ultimately, cash shortages will arise and, either household consumption will have to decrease or financial leverage will have to increase.

From an accounting point of view, balanced growth can aid in making strategic decisions that can help explain observable patterns of consumption, investment and leverage. Such an assessment has not previously been done. In the next section, we examine historical farm accounting data to measure active versus sustainable growth rates and to determine whether or not observable characteristics of the U.S. farm sector conform to a balanced growth paradigm.

Data and Measurement Issues

Our estimates of sustainable and actual business growth rates were obtained from the farm balance sheet and income statement information compiled by the United States Department of Agriculture (USDA) at the state level for the years 1980 to 2001. Sustainable growth rates were derived from measures of farm equity returns, calculated using net worth value at the beginning of each calendar year, and the farm business' earnings retention rate for the year. The latter measure is merely estimated since the USDA's reporting format uses only aggregate financial measures and leaves out details concerning the inflows and outflows to the farm equity account such as non-farm incomes generated, family living withdrawals and both unrealized and realized capital gains from property appreciation and sales, respectively. We therefore used an approximation of the earnings retention rate using information on net farm income realized for the year and the beginning and ending levels of farm net worth. These approximated rates of sustainable growth are then compared to the actual levels of farm revenue growth to generate information on the SGC rates.

National and Regional Rates of Sustainable Growth Challenge

Figure 2 presents a plot of actual growth, sustainable growth and the resulting SGC rates for U. S. farms during the period 1981-2001. The trends indicate a tendency for farms to experience positive SGCs in the 1980s. Interestingly, the farm sector was plagued with declining commodity prices during this period, although farmers continued to receive substantial counter-cyclical subsidies from the government. However, it appears that positive SGCs can be largely attributed to lower rates of sustainable growth, instead of the industry's capacity to generate higher actual revenues, for the farm sector during these years. This is a direct result of the rapid depletion of farm equity, indicative of the severe financial crises experienced by most farm businesses at that time. As far back as the mid to late 1970s, the farm sector's loan to value ratios have increased significantly, thus, enabling farmers to increase asset holdings even with less equity commitment. During this time, farmers were able to monetize their unrealized capital gains as the appreciation of land values allowed farmers to borrow beyond the farm's actual repayment capacity. The dramatic decline of land values in the 1980s, however, ushered in a period of severe financial stress as the real concern for debt repayment capacity surfaced for farm borrowers that incurred debts beyond the affordable limit.

In the 1990s, reforms and conservative credit policies implemented by lenders demanded farmers to make more cautious borrowing decisions. As business expansion plans were more synchronized with actual farm production and financial capabilities, the SGC values in the early to mid-1990s in Figure 2 border along the horizontal axis, suggesting only slight differences between realized and sustainable growth rates. Notably, the SGC values have been negative from 1998-2001, consistent with the steady plunge of farm commodity prices during this period. Moreover, radical changes in federal policy towards agriculture involve a shift from market-based to fixed, decoupled production and price support payments. Although the federal government later disbursed large ad-hoc farm income subsidy appropriations, most farms actually realized lower business growth rates due to perceptions of increased income volatility and uncertainty.

Tables 1, 2 and 3 report actual farm revenue growth rates, estimates of the rate of sustainable growth and the resulting SGC rates, respectively, for the ten production regions in the country. The USDA has actually introduced a newer scheme for classifying counties in each state into major farm resource regions, however, since our data set are aggregated at the state-level we had to resort to the older farm production regional classification system. Hence, the regions considered include the Northeast, Lake States, Corn Belt, Northern Plains, Appalachian, Southeast, Delta States, Southern Plains, Mountains and the Pacific. These groupings were based on state boundaries, with a regional classification assigned to neighboring states with similar production practices and resource characteristics.

Table 4 presents statistical measures for each region to analyze differences in SGC patterns at certain time periods. The summary indicates overall positive mean SGC rates across all regions in the 1980s, with mean SGC rates ranging from 1.52% for the Northeastern states to 8.70% for the Delta States. The relative variability indicators (coefficient of variation) are considerably small, with a high of 3.28% for the Northeastern states and a low of 0.67% for the Mountain states.

In the early 1980s, positive SGC rates are the result of fluctuating actual revenue growth rates (Table 1) and (almost consistently) negative sustainable growth rates (Table 2), experienced especially in the Corn Belt, Appalachian, Lake, Northern Plains and the Southeast regions where grain producers have been most affected by the radical decline of farmland values. During this period, high interest rates and declining export demand led to a nationwide 31% drop in farm real estate values and compounded debt repayment problems for highly leveraged producers. Interestingly, the livestock producers in the Northeast realized positive rates of growth and sustainability for most of this period as the relatively low sensitivity of pastureland to sudden market adjustments of land values spared these producers from the financial influence of the boom-bust cycle of the 70s and 80s.

In the 1990s, the effects of increasing farm income risk due to greater market uncertainty and the changing structure of federal policy towards agriculture are reflected in mixed results obtained for the different regions. The heterogeneity of regional production profiles account for divergent trends in SGC levels.

During the period 1990-1995 when federal payments provided income stabilization benefits, the corn and soybean producers in the Corn Belt and Lake States, who largely benefited from such subsidies, were able to build up excess production capacities as a result of stronger equity positions and debt servicing capabilities. Hence, these farms realized negative average SGC rates, with lower relative variability, during this period.

Elsewhere in the country, the gap between actual and sustainable growth rates was lower when compared to the wider disparity of growth rates realized in the 1980s. Cotton and peanut farmers in the Southeast and Delta states continued to receive federal support, although not by as much as the subsidies appropriated for the grain producers. The dairy, cattle, hog and broiler farmers in the Northeast, Northern Plains, Mountain states and Southern Plains relied on marketing strategies and production alliances to enhance financial conditions resulting in greater access to more sources of capital.

As federal farm support veered away from a market-oriented type of subsidy and agricultural commodity prices declined steadily in the latter part of the 1990s, mean SGC rates still remained close to 1 although relative variability increased considerably in 6 of 10 regions.

Preliminary Analysis of Balanced Growth Strategies

This section presents a cursory analysis of relationships between the historical levels of SGC rates and several variables included in the sustainable growth paradigm. Figure 3 presents the trends in the SGC rates and debt-to-asset ratios, decomposed into long-term and non-long-term components, for all US farms during the period 1981 to 2001. The financial leverage ratios were derived from the aggregate balance sheets compiled by the USDA-ERS for all U. S. farms during the 21-year period. The long-term leverage measures were calculated as the ratio of total farm real estate debt to the total market value of farm real estate asset holdings for each year. The shorter-term measures were calculated by dividing the total levels of intermediate and short-term loans by the sum of the total value of non-real estate assets, including crop and livestock inventories, machineries and equipment, purchased inputs and financial assets.

In order to discern clear patterns of relationships between the measures presented in Figure 3, a summary is presented in Table 5 of the results of basic correlation analysis performed on pairs of values of SGC rates and, among other variables, values of each of the two leverage measures over certain time frames. The graphs and derived correlation measures indicate that both long- and non-long term measures of financial leverage are positively correlated with changes in SGC rates over the entire 21-year period, differing in magnitude of the correlation coefficients by only 5 percentage points at 0.4976 and 0.4476, respectively. Significant deviations in correlation results are obtained, however, when different (shorter) time periods are considered. In the 1980s, positive correlation between both financial leverage measures and SGC is maintained, although the shorter-term measure has a higher correlation coefficient at 0.3269 (versus 0.2095 for the long-term variable). As noted earlier, farmers exhibited an aggressive borrowing behavior in the 1980s as farmland values appreciated. Viewed in terms of the sustainable growth paradigm, farms in general resorted to financial leveraging as a means of increasing liquidity and production capacity build-up during such period, with a greater tendency to resort to intermediate- and short-term loans vis-à-vis longer-term loans. The latter result could suggest that short-term liquidity, instead of fixed asset accumulation, was a more pressing concern among farm businesses at that time and farms relied on short- and intermediate-term loans to address this need.

In the nineties, there was a diminishing reliance on financial leveraging to boost sustainable growth potential, given the low and negative correlation results (Table 5) for non-long-term and long-term financial leverage measures, respectively. During this period, the propensity to incur loans among farmers has been regulated by stricter credit risk assessment and credit rationing policies by lenders. Thus, more cautious borrowing decisions were made. The results also implied that financial leveraging could have been avoided by some farmers whenever opportunities to implement alternative strategies to improve sustainable growth rates were available.

The other correlation results in Table 5 and the plots presented in Figure 4 for historical levels of net profit margin (NFIRAT) and asset turnover (ATO) ratios suggest that during times of restrictive credit environments the farmers resorted to other strategies to increase sustainable growth potentials. In the eighties when farmers relied more on financial leveraging to increase sustainable growth rates, NFIRAT and ATO produced negative correlations with SGC. During this time, increased financial and operating inefficiency resulted in profit margin squeezes while the maintenance of excess production capacities through building up inventories of idle, obsolete and unproductive assets brought down the farm sector's ATO rates.

In the nineties profit margins and asset productivity became important tools for attaining higher rates of sustainable growth as the NFIRAT and ATO were found to be highly correlated with SGC rates at 0.7302 and 0.5818, respectively. More favorable market conditions in the early part of the decade, the availability of more efficient production technologies (i.e. the introduction of GMOs), and the implementation of risk-reducing marketing plans all contributed to the attainment of more acceptable profit margins. The prevalence of real estate and equipment leasing contracts as well as the implementation of more prudent asset management strategies aimed at eliminating idle production capacity did not only result in improved ATO ratios but also provided additional liquidity-enhancing mechanisms for some farms through cash proceeds from asset liquidation and the more favorable expense disbursement schemes available under certain land leasing arrangements.

While this analysis does not include the liquidity implications of changes in equity withdrawals for farm household consumption due to data limitations, it can be clearly seen that, over the time frame considered, the significance/insignificance of strategies that involve financial leveraging, income efficiency and asset productivity alternately complement each other to modify a farm's sustainable growth potential in order to achieve balanced growth.

Conclusions

This paper has presented a different approach to examining certain aspects of agriculture finance by introducing the concept of sustainable growth as presented by Higgins (1972, 2001). The sustainable growth model requires a balance between increased sales at the farm level and changes in corresponding accounting measures such as profit margin, owner withdrawals or business retention rates, asset turnover, and financial leverage. We argue that this paradigm can be used to explain observed financial and operating conditions in agriculture. In particular, we note that when farm revenues increase above a measured sustainable growth rate, there is also a tendency for farm debt to increase, and when revenues fall, there is a tendency for farm debt to decrease. But the role of debt is not so simply related to increases in sales. Household consumption expenditures, represented by owner withdrawals, also play a role. As expenditures increase due to inflation, the retention ratio and sustainable growth falls, relative to sales. This condition increases the pressure on cash flow and increased use of debt. Likewise, in periods of inflationary land values, as turnover falls and if sustainable growth falls relative to sales, cash shortages need to be absorbed through either restrictions in household expenditures or increased use of debt.

This study has provided estimates of actual and sustainable growth rates from 1981 to 2001 for the seven producing regions in the United States and discusses these within the context of the agriculture economy. Our analyses show a general contribution to the sustainable growth paradigm.

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Table 1. Average Rates of Actual Revenue Growth of U.S. Farms (Percent), By Region, 1981-2001											
Year	APL[1]	CB[2]	DS[3]	LS[4]	MTNS[5]	NE[6]	NPLNS[7]	PCFC[8]	SE[9]	SPLNS[10]	All States
1981	14.46	10.98	16.20	7.98	-0.15	12.63	16.90	2.06	16.53	13.16	11.42
1982	-1.37	-3.90	-2.56	0.14	-1.81	4.49	4.38	4.38	-1.27	0.92	-1.31
1983	-8.47	-15.53	-4.30	-6.82	1.72	1.67	-3.94	8.86	-4.66	-4.60	-6.27
1984	12.34	21.29	8.33	7.67	-0.58	1.62	9.84	-1.01	9.05	-0.24	9.18
1985	-9.28	-2.10	-9.34	-5.18	-6.16	-1.20	-1.48	-3.10	-6.98	-2.41	-4.02
1986	-4.84	-6.76	-9.29	-3.49	2.27	0.39	-4.09	6.95	-5.01	-0.87	-3.15
1987	7.70	4.01	17.61	5.49	10.90	5.01	5.48	6.69	13.26	9.96	7.86
1988	8.48	1.72	16.63	-1.56	9.50	5.71	1.82	6.17	12.14	11.44	5.64
1989	7.89	12.82	1.30	17.34	7.14	4.71	3.95	4.75	12.99	1.89	7.85
1990	3.86	0.08	-0.11	-1.08	4.58	2.89	11.30	2.95	-8.36	7.60	3.22
1991	-0.68	-7.83	2.51	-5.05	-0.26	-3.46	-5.66	-2.04	7.25	-1.24	-3.09
1992	7.03	11.99	5.67	0.03	-2.65	5.53	7.76	1.35	-1.10	-0.40	4.50
1993	2.79	-3.61	2.05	-1.06	13.95	-1.17	-2.45	9.90	2.36	6.96	2.22
1994	5.70	8.88	9.17	10.72	-3.93	4.35	7.01	4.54	8.89	1.84	5.36
1995	-1.77	-7.43	-3.00	-1.56	2.38	-2.60	-7.84	0.59	-0.99	-5.70	-2.45
1996	7.19	20.99	16.65	9.55	4.76	7.02	22.65	7.89	9.58	-0.58	11.86
1997	1.66	0.74	-5.06	-1.22	6.92	-3.32	-6.82	3.04	2.15	13.49	1.00
1998	0.20	-6.75	-4.73	1.89	-0.03	2.10	3.55	-3.15	-0.44	-7.10	-2.53
1999	-3.62	-4.97	5.47	1.17	3.75	-0.63	-0.35	1.40	2.18	12.47	1.02
2000	12.48	9.35	-6.90	-1.86	2.94	3.42	6.36	4.37	-0.90	-2.55	3.09
2001	-2.76	1.97	7.58	2.64	4.34	0.66	0.16	-0.50	6.52	1.97	1.99

Notes: (1) The Appalachian states include Kentucky, North Carolina, Tennessee, Virginia and West Virginia; (2) The Corn Belt states include Illinois, Indiana, Iowa, Missouri and Ohio; (3) The Delta States are Arkansas, Louisiana and Mississippi; (4) The Lake States are Michigan, Minnesota and Wisconsin; (5) The Mountain States are Arizona, Colorado, Idaho, Montana, Nevada, New Mexico, Utah, and Wyoming; (6) The Northeast Region includes Connecticut, Delaware, Maine, Maryland, Massachusetts, New Hampshire, New Jersey, New York, Pennsylvania, Rhode Island and Vermont; (7) The Northern Plains includes Kansas, Nebraska, North Dakota and South Dakota; (8) The Pacific Region includes Alaska, California, Hawaii, Oregon and Washington; (9) The Southeast Region includes Alabama, Florida, Georgia and South Carolina; and (10) The Southern Plains includes Oklahoma and Texas.

Table 2. Average Rates of Sustainable Growth of U.S. Farms (Percent), By Region, 1981-2001											
Year	APL[1]	CB[2]	DS[3]	LS[4]	MTNS[5]	NE[6]	NPLNS[7]	PCFC[8]	SE[9]	SPLNS[10]	All States
1981	-2.06	-9.98	-4.44	-3.36	0.52	1.28	-0.89	3.27	-6.58	2.45	-2.03
1982	-2.04	-10.33	-9.64	-5.73	-5.12	-2.47	-5.79	0.57	-3.69	-2.11	-5.51
1983	-0.66	-3.34	0.53	-3.65	0.54	1.49	-3.70	0.02	-3.38	1.17	-0.46
1984	-7.75	-22.54	-8.96	-15.99	-9.43	0.56	-19.38	-7.48	-5.76	-8.46	-11.84
1985	-2.64	-10.30	-13.15	-13.24	-11.48	2.59	-11.51	-5.24	-2.81	-14.48	-10.27
1986	-1.05	-5.47	-12.77	-8.81	-2.53	4.57	-6.08	-8.85	0.98	-6.26	-4.59
1987	-0.44	5.43	3.51	8.21	0.84	5.53	7.66	-0.22	5.73	3.12	6.59
1988	2.84	3.74	1.81	3.96	1.46	5.92	5.35	4.33	6.01	0.95	6.04
1989	3.06	2.91	-0.59	6.12	0.48	1.91	3.95	5.31	6.36	0.13	4.27
1990	-0.27	3.89	2.59	6.26	4.10	-1.77	2.77	5.23	1.41	0.39	3.86
1991	2.51	0.70	-2.74	0.55	0.19	-0.71	-2.09	-0.87	0.15	0.46	0.33
1992	4.71	3.47	2.81	3.22	-4.24	6.47	2.10	1.67	3.94	4.52	3.37
1993	2.33	2.88	2.81	-0.05	6.78	-0.79	3.93	2.69	3.97	2.98	5.28
1994	5.13	3.57	3.43	2.18	2.74	0.05	1.87	0.54	5.07	1.13	2.70
1995	3.13	2.36	2.66	3.28	2.59	-0.12	1.14	1.73	1.89	-2.13	3.43
1996	2.97	5.33	0.21	3.26	2.42	0.13	4.94	2.19	1.72	2.45	3.92
1997	2.88	4.93	4.19	1.71	3.13	-1.76	3.79	0.81	3.71	4.82	4.61
1998	0.62	2.66	4.16	3.57	0.06	2.24	-0.29	2.41	2.90	0.21	2.78
1999	2.96	1.96	4.18	4.55	3.49	-2.49	5.12	0.73	2.50	3.12	5.07
2000	5.53	2.65	1.29	2.63	2.43	3.78	3.33	1.55	5.91	4.88	4.98
2001	2.15	2.22	1.78	1.89	1.16	2.82	1.34	1.20	5.39	4.34	3.59

Notes: (1) Appalachian; (2) Corn Belt; (3) Delta States; (4) Lake States; (5) Mountain States; (6) Northeast; (7) Northern Plains; (8) Pacific; (9) Southeast; and (10) Southern Plains.

Table 3. Average Rates of Sustainable Growth Challenge of U.S. Farms (Percent), By Region, 1981-2001											
Year	APL[1]	CB[2]	DS[3]	LS[4]	MTNS[5]	NE[6]	NPLNS[7]	PCFC[8]	SE[9]	SPLNS[10]	All States
1981	16.52	20.96	20.63	11.34	-0.67	11.35	17.79	-1.21	23.11	10.72	13.45
1982	0.68	6.43	7.09	5.87	3.31	6.96	10.17	3.81	2.42	3.03	4.20
1983	-7.81	-12.20	-4.83	-3.17	1.18	0.18	-0.24	8.84	-1.28	-5.78	-5.81
1984	20.09	43.84	17.29	23.66	8.85	1.06	29.22	6.47	14.80	8.23	21.02
1985	-6.64	8.20	3.82	8.05	5.33	-3.80	10.03	2.14	-4.16	12.07	6.25
1986	-3.79	-1.29	3.49	5.32	4.81	-4.18	1.99	15.80	-5.98	5.39	1.45
1987	8.14	-1.41	14.09	-2.71	10.06	-0.52	-2.17	6.91	7.54	6.84	1.27
1988	5.64	-2.03	14.82	-5.52	8.04	-0.21	-3.53	1.84	6.12	10.49	-0.41
1989	4.83	9.91	1.88	11.22	6.66	2.80	0.01	-0.56	6.64	1.76	3.58
1990	4.13	-3.81	-2.71	-7.34	0.48	4.66	8.53	-2.28	-9.78	7.21	-0.64
1991	-3.19	-8.52	5.25	-5.60	-0.45	-2.76	-3.57	-1.18	7.10	-1.70	-3.41
1992	2.32	8.53	2.86	-3.18	1.59	-0.94	5.66	-0.32	-5.04	-4.93	1.13
1993	0.45	-6.49	-0.75	-1.01	7.18	-0.38	-6.38	7.21	-1.61	3.98	-3.06
1994	0.58	5.31	5.74	8.54	-6.66	4.29	5.15	4.00	3.81	0.71	2.66
1995	-4.90	-9.79	-5.66	-4.85	-0.21	-2.48	-8.98	-1.14	-2.88	-3.57	-5.88
1996	4.23	15.65	16.44	6.29	2.33	6.88	17.71	5.69	7.87	-3.04	7.94
1997	-1.22	-4.19	-9.26	-2.93	3.78	-1.56	-10.61	2.24	-1.56	8.68	-3.61
1998	-0.42	-9.41	-8.89	-1.68	-0.08	-0.15	3.85	-5.56	-3.33	-7.32	-5.31
1999	-6.58	-6.93	1.30	-3.38	0.26	1.86	-5.46	0.67	-0.32	9.36	-4.05
2000	6.96	6.70	-8.19	-4.48	0.52	-0.36	3.03	2.82	-6.81	-7.43	-1.89
2001	-4.91	-0.24	5.80	0.75	3.18	-2.17	-1.18	-1.69	1.14	-2.37	-1.60

Notes: (1) Appalachian; (2) Corn Belt; (3) Delta States; (4) Lake States; (5) Mountain States; (6) Northeast; (7) Northern Plains; (8) Pacific; (9) Southeast; and (10) Southern Plains.

Table 4. Summary Statistics for SGC Rates, By Region, Selected Time Periods, in Percent											
Time Period	APL[1]	CB[2]	DS[3]	LS[4]	MTNS[5]	NE[6]	NPLNS[7]	PCFC[8]	SE[9]	SPLNS[10]	All States
1981-2001											
Mean	1.67	2.82	3.82	1.68	2.83	0.98	3.38	2.59	1.80	2.49	1.85
Std. Dev.	7.25	12.90	8.91	7.77	3.96	3.95	9.75	4.77	7.76	6.42	6.52
C. V.	4.34	4.57	2.33	4.64	1.40	4.03	2.88	1.84	4.31	2.58	3.52
1980-1989											
Mean	4.18	8.05	8.70	6.01	5.28	1.52	7.03	4.89	5.47	5.86	6.29
Std. Dev.	9.75	16.36	8.41	9.12	3.56	4.97	10.90	5.32	9.24	5.60	6.83
C. V.	2.33	2.03	0.97	1.52	0.67	3.28	1.55	1.09	1.69	0.96	1.09
1990-1995											
Mean	-0.10	-2.46	0.79	-2.24	0.32	0.40	0.07	1.05	-1.40	0.28	-1.53
Std. Dev.	3.38	7.61	4.58	5.70	4.43	3.28	7.28	3.73	6.08	4.64	3.17
C. V.	-33.24	-3.09	5.82	-2.55	13.84	8.23	107.24	3.56	-4.35	16.38	-2.07
1996-2001											
Mean	-0.33	0.26	-0.47	-0.91	1.67	0.75	1.22	0.69	-0.50	-0.35	-1.42
Std. Dev.	5.19	9.42	10.35	3.95	1.65	3.31	9.72	3.92	4.93	7.56	4.79
C. V.	-15.91	35.68	-22.13	-4.36	0.99	4.40	7.95	5.65	-9.83	-21.49	-3.37

Notes: (1) Appalachian; (2) Corn Belt; (3) Delta States; (4) Lake States; (5) Mountain States; (6) Northeast; (7) Northern Plains; (8) Pacific; (9) Southeast; and (10) Southern Plains.

Table 5. Correlation of SGC Rates and Relevant Financial Measures, U. S. Farms, Selected Time Periods			
Financial Measure paired with SGC	Correlation Coefficients		
	1981-2001	1981-1989	1990-2001
Net Farm Income Ratio	-0.2465	-0.0526	0.7302
Asset Turnover Ratio	0.0517	-0.0598	0.5818
Long-Term Debt-Fixed Farm Asset Ratio	0.4976	0.2095	0.0746
Non-Long-Term Debt-Non-Fixed Farm Asset Ratio	0.4476	0.3269	-0.2158

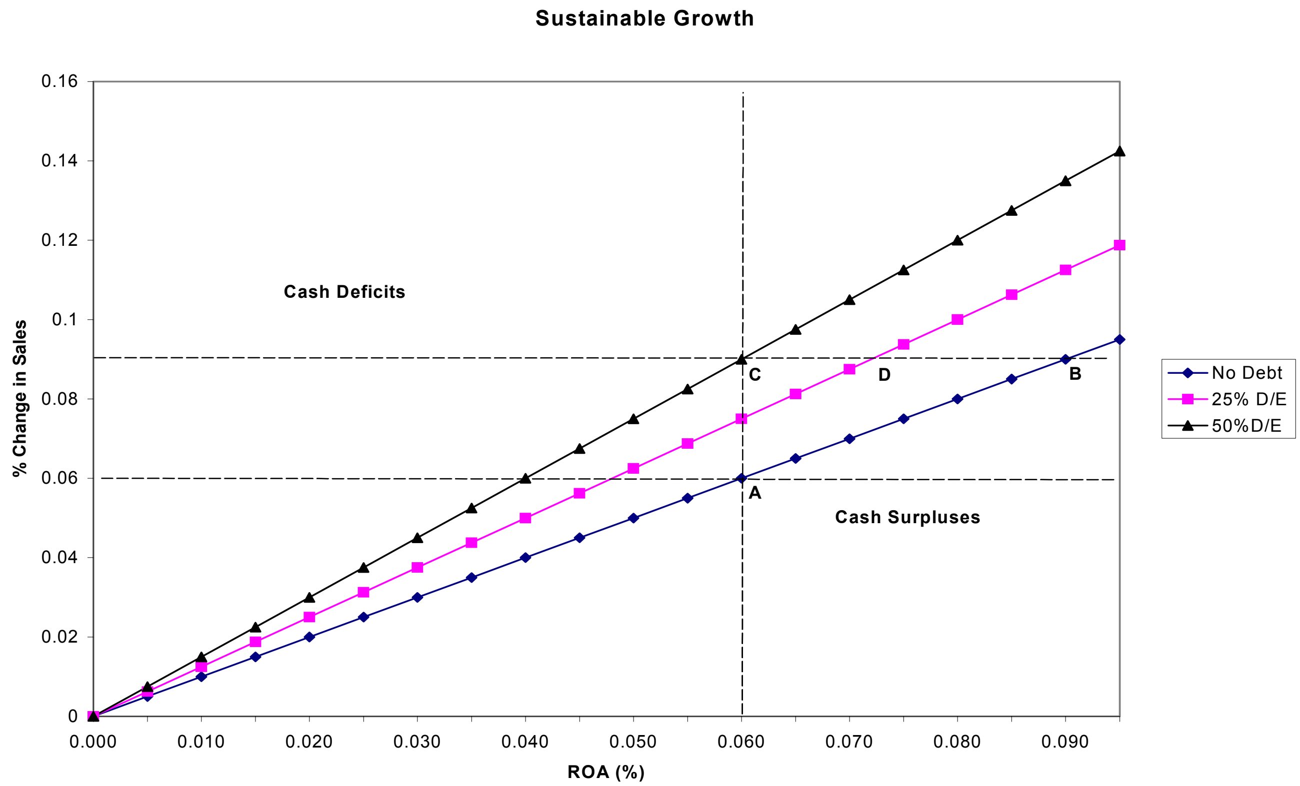
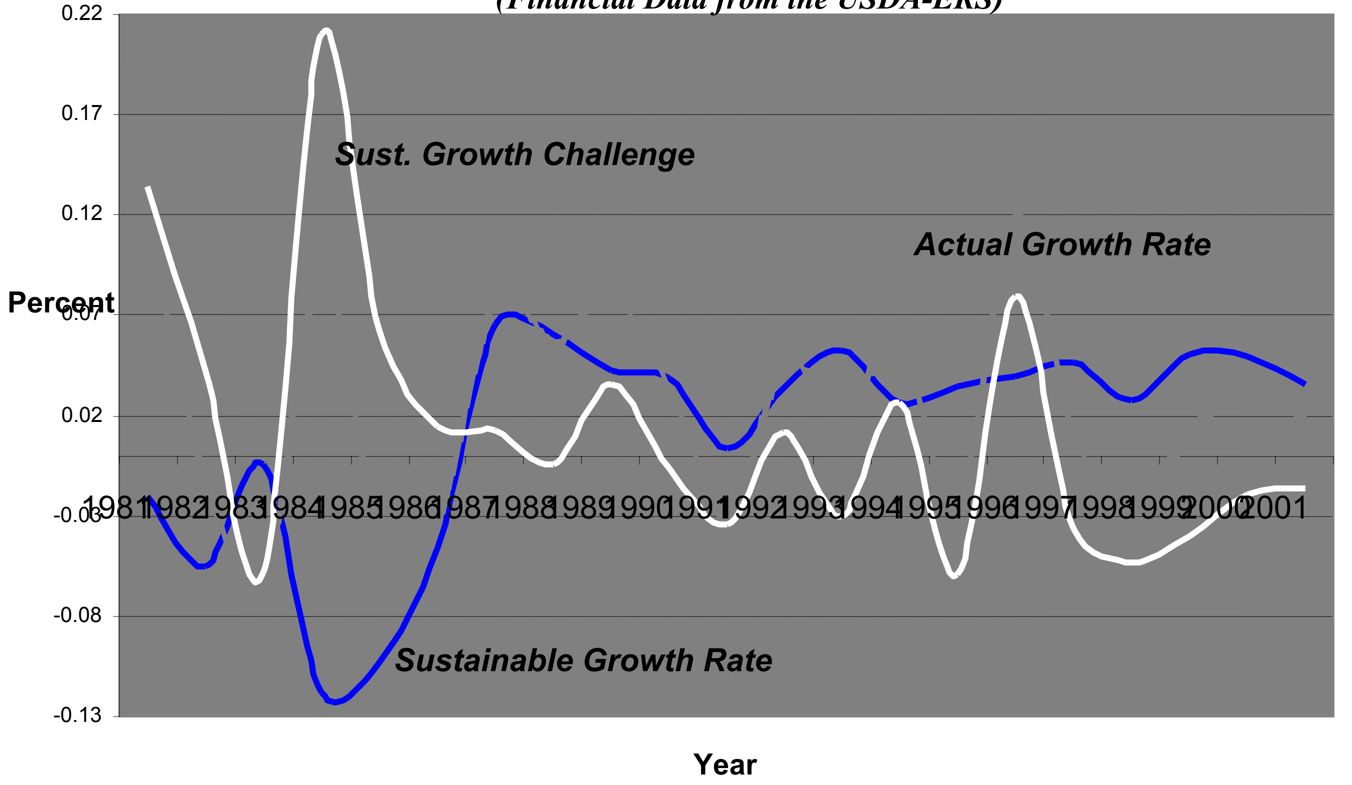


Figure 1: A Graphical Depiction of Sustainable Growth

Figure 2. Rates of Actual Growth, Sustainable Growth and Sustainable Growth Challenge, U. S. Farms, 1981-2001
(Financial Data from the USDA-ERS)



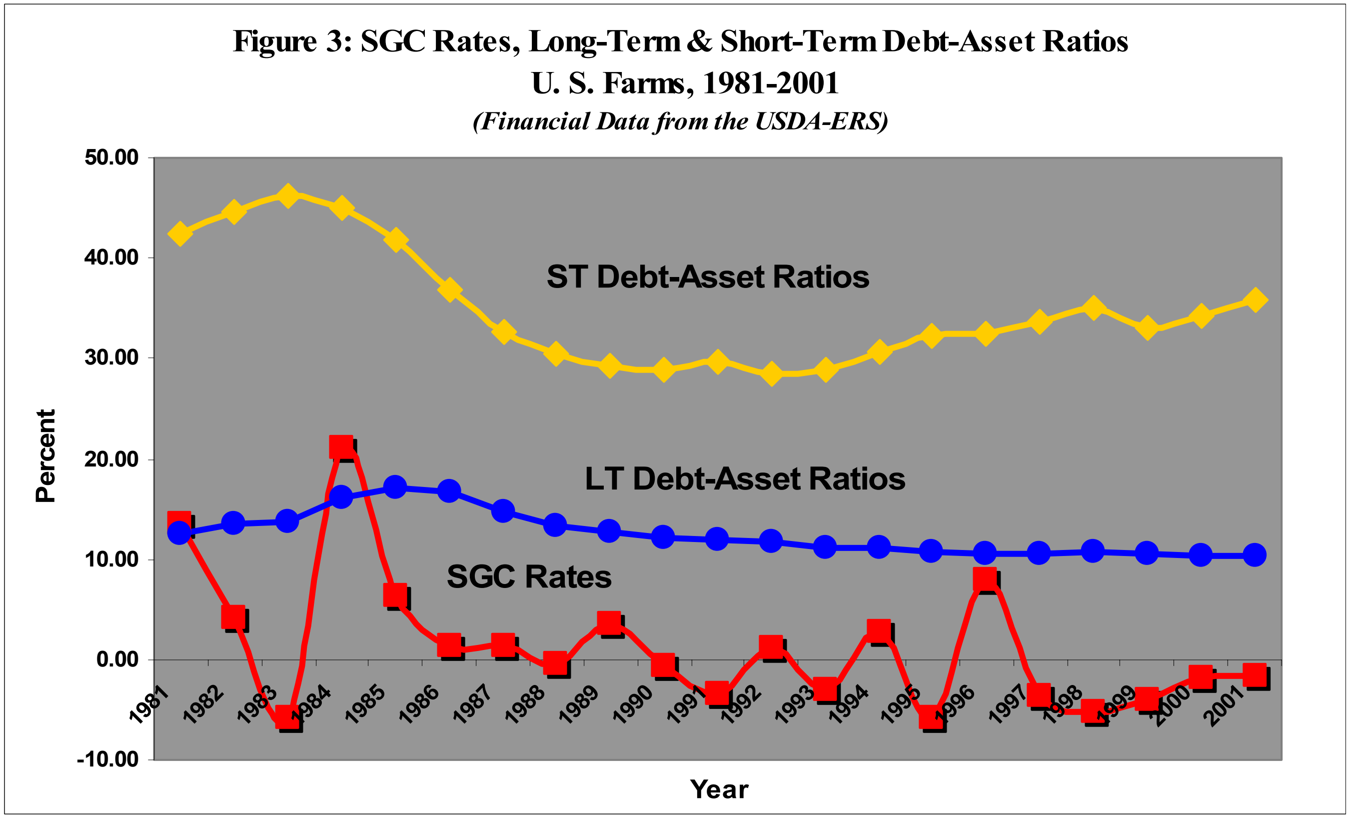
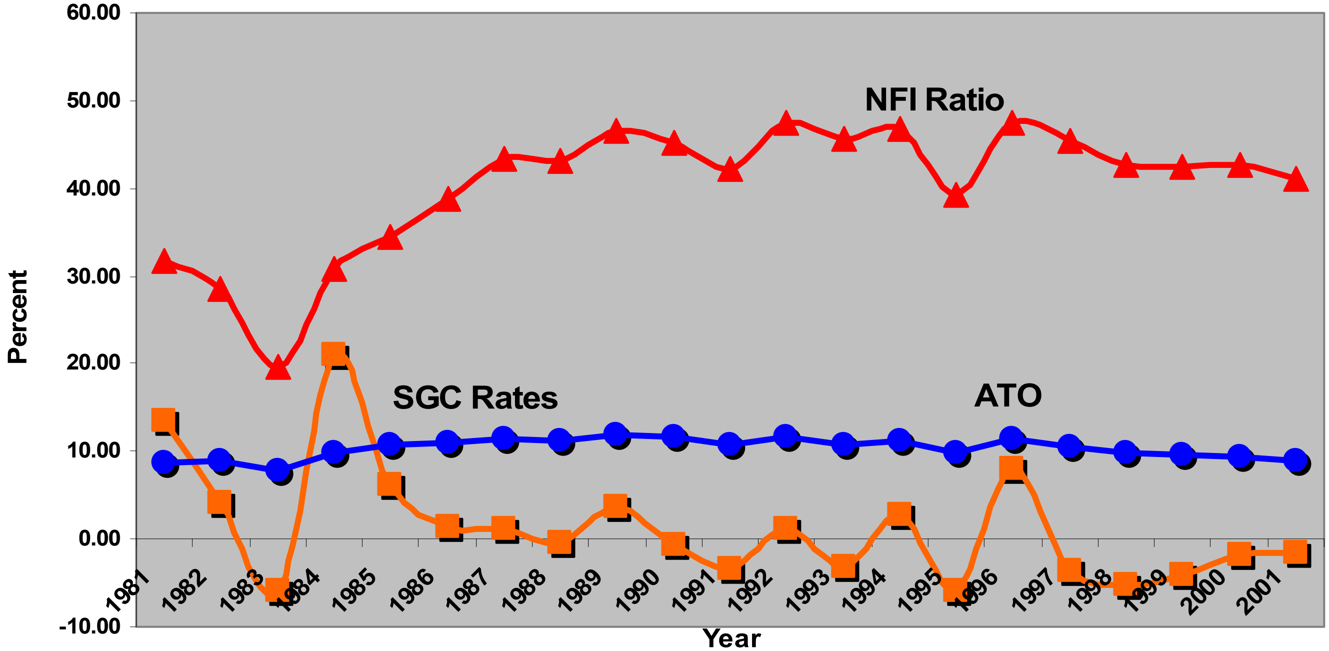


Figure 3: SGC Rates, Long-Term & Short-Term Debt-Asset Ratios
U. S. Farms, 1981-2001
(Financial Data from the USDA-ERS)
50.00
40.00
30.00
20.00
10.00
0.00
-10.00
Percent
ST Debt-Asset Ratios
LT Debt-Asset Ratios
SGC Rates
1981
1982
1983
1984
1985
1986
1987
1988
1989
1990
1991
1992
1993
1994
1995
1996
1997
1998
1999
2000
2001
Year

Figure 4. Net Farm Income (NFI) Ratios, Asset Turnover Ratios (ATO) and Sustainable Growth Challenge (SGC) Rates, U. S. Farms, 1981-2002

(Financial Data from the USDA-ERS)



Evaluating USDA Forecasts of Farm Assets: 1986-2002

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Evaluating USDA Forecasts of Farm Assets: 1986-2002

Introduction

Short-term USDA balance sheet forecasts include six different asset categories (real estate, livestock and poultry, machinery and motor vehicles, crops stored, purchased inputs, and financial assets). The USDA forecast of farm sector total assets is the sum of its forecasts for these six different asset categories. We evaluate the USDA forecasts of farm sector total assets from the perspective of forecast consumers of the USDA's monthly *Agricultural Outlook.* More specifically, we test whether:

- forecast accuracy of farm sector total assets improved over 1986-2002;
- the updating processes result in more accurate predictions;
- past forecast errors provide a basis to issue better future forecasts; and
- the reliability of the USDA forecasts' exceeds that of forecasts issued by a CPI-based model.

How Accurate are USDA Forecasts?

Previous research on USDA forecast accuracy has emphasized forecasts of farm commodities. USDA evaluation of its own forecasts has generally concluded their forecast models are inefficient, with mixed results regarding forecast bias. As time progresses towards the date of the forecasted event, the number of unknown factors declines. Hence updating forecasts over time reflecting new information and improved data should result in better forecasts. Updating forecasts by the USDA has been shown to improve forecast accuracy. Surls and Gajewski found wheat forecasts the most accurate of the USDA's domestic grain production forecasts. Forecasts of domestic production were unbiased while forecasts of foreign coarse grain production were generally biased. They found dramatic improvements in forecast accuracy as forecasts were updated on a monthly basis. Forecasts of U.S. agricultural exports, although unbiased, experience a larger forecast error than forecasts of U.S. agricultural production. This is unsurprising given that forecasts of exports depend on predictions of exchange rates and the politically-drive decisions of many different countries. USDA forecasts of ending stocks, a residual between forecasts of production and use, have the largest forecast error. Denbaly et al. showed that monthly forecasts of seven components of the Bureau of Labor Statistic's food CPI series generated from an ARIMA model were more accurate than forecasts computed by the USDA.

Research in the academic community has generally arrived at similar conclusions as the USDA. Gunnelson, Dobson, and Pamperin found the USDA tends to underestimate annual crop size when forecasting potatoes, winter wheat, and spring wheat. They found USDA's first forecasts were superior to a naïve forecast and that updating forecasts improved accuracy. Baur and Orazem found the USDA's forecasts of orange production to be unbiased and efficient from 1973-1992. Irwin, Gerlow, and Te-ru Liu found no meaningful difference between the accuracy of forecasts issued by the USDA for livestock or those based on the futures price from 1980 through 1991. Kastens, Schroeder, and Plain found extension forecasts to be more accurate than USDA forecasts for livestock but not crops from 1983-1995. Forecasts from the American Agricultural Economics Association's (AAEA) Annual Outlook Survey are more accurate than USDA forecasts for both livestock and crops. Bailey and Brorsen found that the USDA underestimated production and supply for beef and pork from 1982-1989. During 1990-1996 this bias disappeared and forecast variance declined such that USDA forecasts in the last few years of the study period were deemed as optimal forecasts. However, Sanders and Manfredo found that USDA forecasts quarterly forecasts of beef, pork, and poultry production over 1982 through 2000 did not improve over time, failed to incorporate information contained in past forecasts, and were inefficient. They did conclude that the USDA forecasts are unbiased and more accurate than those produced by a simple autoregressive time-series model. Egelkraut et al. found the USDA's forecast errors regarding monthly corn production are unbiased and generally smaller than those for two private forecast agencies from 1971-2000. Results were mixed for soybean production. Updating forecasts improved the USDA's forecast accuracy as the crop year progressed.

Data

Estimates or Actuals: Initial and Revised

The USDA issues its first, initial estimate of total farm sector assets for December 31st of each year about a year after the date being estimated. The lag between the December 31st date being estimated and the actual date the initial estimate is issued (i.e., published in *Agricultural* Outlook) ranged from 4 to 25 months from 1986-2001, averaging about 13 months. For example, the USDA's first or initial estimate of farm sector total assets for December 31, 2001 was issued in December 2002. Following the issuance of its initial estimate of total farm assets, the USDA continues to issue revised estimates in the future as more and better data become available. We contrast both the USDA's initial and most recently revised estimates of actual total farm assets as of December 31st for each year from 1986-2001 against the USDA's time series of predictions. *Agricultural Outlook* ceased publication in December 2002.

Predictions: Forecasts and Backcasts

The USDA issues its first prediction in the first quarter of the forecasted year. Predictions are updated over time throughout the forecasted year and usually continue well into the following year, ending just before the USDA publishes its first or initial estimate. We refer to predictions made before the December 31st date of the predicted year as forecasts. Predictions issued after the December 31st date are referred to in the paper as backcasts.

For example, the first prediction for the total farm sector assets for December 31, 2001 was presented at the World Agricultural Outlook Forum in late February 2001 and published in Agricultural Outlook in March 2001. This prediction is referred to in our paper as the first forecast. During 2001 the USDA issued three more forecasts for total assets for December 31, 2001 (in June, September, and December 2001). The initial prediction and the three updated predictions issued during 2001 for the level of total farm assets for December 31, 2001 are referred as forecasts. During 2002, the USDA issued three more predictions in April, August, and September for total farm assets for December 31, 2001. These three predictions issued in 2002 after the forecasted date (December 31, 2001) are backward-looking predictions or backcasts. In December, 2002, the USDA issued its first or initial estimate of total farm assets for December 31, 2001.

Thus 7 predictions for total farm assets on December 31, 2001 were issued over a 2-year period. The first 4 predictions were issued in March, June, September, and December of 2001. These four predictions are referred to as *forecasts*. The latter 3 predictions for total farm assets on December 31, 2001 were issued in April, August, and September of 2002. These latter 3 are referred to as *backcasts*, in that they were issued after the forecasted date (December 31, 2001) but before the USDA issues its first estimate during December 2002.

From 1986 through 2001, 11 of the 16 first forecasts are issued in January of the forecast year, with a total of 14 being issued by March. The other two first forecasts were issued in June and October of the forecasted year. Predictions issued after the December of the forecast year are referred to in our paper as *backcasts*. The final backcast is usually issued late in the following year but still prior to the USDA's issuance of its initial estimate for the previous year. Two of the final 16 backcasts are issued in the first half of the following year. The other fourteen are issued in the latter half of the following year.

The USDA made as many as 8 forecasts for a particular year (1986) to as few as 4 forecasts for a particular year. There were a total of 91 forecasts made for the 16 different years from 1986-2001. About half of the 91 predictions are issued prior to December of each year (thereby being classified as forecasts) while the other half are issued after December of the year of the forecast (thereby being classified as backcasts).

Both the forecasts and estimates are obtained from various issues of the USDA's *Agricultural Outlook* from 1986 through 2002.

Evaluating Forecast Accuracy

Forecast Error (E) is defined as the difference between the USDA's estimate of actual total assets (A) and the USDA's prediction (F) of total farm assets; E = A - F. Forecast errors are calculated using both the initial estimate and a recent revised estimate of farm sector total assets.

Four statistics are used to measure the USDA's out-of-sample forecast performance of farm sector total assets: the mean error (ME), the mean absolute error (MAE), the root mean squared error (RMSE), and the mean absolute percentage error (MAPE). The larger these measures of forecast evaluation, the greater the model's typical forecast error and the less accurate and reliable is the model's forecasts.

The CBO uses *mean error* ME, the arithmetic average of all the forecast errors, to measure statistical bias in its forecasts. ME is likely to be small since positive and negative errors tend to offset each other. While ME indicates if there is systematic under- or over-forecasting, it indicates little about the size of the typical forecast error.

The CBO uses MAE and the RMSE to measure the accuracy of its forecasts. The MAE is the average of forecast errors without regard to arithmetic signs. The MAE measures the average distance between forecasts and actual values or estimates without regard to whether the forecasts are too high or too low. The RMSE is the square root of the arithmetic average of the squared errors. The RMSE also shows size of forecast error without regard to sign, but it gives a larger weight to larger forecast errors.

Each of the above statistics is a measure of accuracy whose size is affected by the scale of the data. This creates problems when making comparisons across different time periods. This problem in making comparisons over time can be handled by using the mean absolute percentage error (MAPE) measure. Both RMSE and MAPE are measures of dispersion of the forecast error and are the most commonly used criteria in forecast evaluations (Makridakis; Armstrong and

Collopy). RMSE is the most commonly used criteria in the agricultural economics literature (Allen).

Another means of evaluating a forecaster is the *informational efficiency* of its forecasts. If additional information at the forecaster's disposal when the forecast was made could have been used to improve the forecast, then the forecaster is regarded as informationally inefficient. For example, if an alternative model issues superior forecasts to Model X, then Model X can be said to be inefficient.

A commonly used means of measuring informational efficiency is to contrast the accuracy of forecasts issued by the forecast model of concern to those issued by other forecast models. For example, the Congressional Budget Office contrasts the bias and accuracy of its forecasts to those issued by the *Blue Chip Forecasts* and the Administration's forecasts. Another approach is to contrast forecasts issued by the model of concern to those issued by a naïve model. A naïve no-change model is one which assumes the best expectation of the next unknown value is the currently known value.

Econometric and univariate forecast models often do badly when contrasted to naïve models (Allen). Mechanical forecast models like the naïve model or various rules-of-thumb issue low-cost forecasts that do not require an expert's advice. A minimum criterion for expert forecasters is that they issue forecasts which are more accurate than those issued by a naive forecaster.

Evaluating USDA Forecasts of Farm Assets

Tomek notes that data provided by government agencies are subject to frequent revision. He suggests that models should be run with both the original and revised data sets to see what role, if any, data revisions play in appraising results. Following Tomek's suggestion, we test the accuracy of the USDA's forecasts using both the USDA's initial estimate and the most recently revised USDA estimates of total farm assets from 1986-2002.

We trisect the times series of estimates and forecasts into three periods (1986-1989; 1990-1995; and 1996-2001) in order to determine if the USDA has improved forecast accuracy over time. We compare USDA forecast accuracy to its backcast accuracy to determine if updating USDA predictions results in more accurate predictions. We use a rolling measure of bias in the USDA's forecasts to see if this information can be used to improve future USDA forecasts.

We contrast the USDA forecasts to the forecasts issued by a naive model that assumes each year's farm sector assets is equal to the most recently observed initial estimate of farm sector assets plus an inflation premium. The inflation factor represents the change in the CPI expected to occur between the two initial estimates of farm assets. The most recent one-, two-, or three-year change in the CPI that would have been known to the USDA forecasters at the time the naïve model makes its forecast is used as the expected inflation premium. The naive model issues its forecasts in January of the forecasted year. Due to the USDA lag between the date of the forecasted event and the date the initial estimate is published, there is at least a two-year difference between the most recently observed initial estimate and the forecasted estimate. For example, in January of 1990 the naive model uses the initial estimate for 1988 in its forecast for the December, 31, 1990 estimate of total assets. In January of 1990, the most recently observed two-year percentage change in the CPI is used to convert the 1988 initial estimate to obtain the naïve model's forecast for 1990. In 5 of the 14 forecasted years, there is a two-year lag. In seven of the

14 forecasted years, there is a three-year lag. In the 7 years that use a three-year lagged initial estimate to issue its forecast, the forecast is updated later in the year when the newer, two-year lagged initial estimate is issued by the USDA. The naïve model's forecasts for the initial estimates are the same as for the revised estimates. Because of the lag between the date of the forecasted event (December 31st of each year) and the USDA issuing the initial estimate, forecasts are for the years 1988-2001.

We also contrast the USDA's backcasts to backcasts issued by a naive model. This naive model's backcasts for total farm assets are issued in February of the following year and are updated only twice, once in 1994 (September) and again in 2000 (March). In 1994 and 2000, this one-year lagged initial estimate was not yet available, hence the first backcast is the initial estimate two years before the backcasted year plus the two-year inflation rate. When the initial estimate for the year preceding the backcasted year becomes known later in the year, the backcast is updated by substituting the one-year lagged initial estimate and a one-year inflation premium is added.

For 13 of the 15 backcasts, the first backcast by the naive model is based on the initial estimate of the year preceeding the backcasted year plus the actual inflation rate (which is known by the date of the backcast) between those years. Seventeen forecasts in all are issued by the naive model over 1987-2001 with the initial backcast occurring in February for 1988-2001 and in March for 1987.

Results

USDA Forecast Accuracy 1986-2002

Table 1a shows the four forecast criteria for the three periods where the revised estimate of farm sector total assets is our forecasted "actual." The column heading "FOR" gives the number of forecasts evaluated in each of the three periods. A decline in the forecast evaluation scores indicates an improvement in forecast accuracy over time.

The four statistical evaluation results do not indicate an improvement in forecast performance over time. The best period for all four forecast criteria was 1990-1995. However, the MAPE (4.5) for 1996-2001 is smaller than the MAPE (4.95) for 1986-1989, indicating some improvement over time when the increase in the total assets over time is taken into account.

Table 1b shows the same patterns exists when the initial estimate of farm sector total assets is used as our "actual." These scores are lower than their equivalent scores in Table 1a, indicating that the USDA forecasts are a more accurate indicator of the USDA's initial estimate than its later revised estimate.

Updating USDA Forecasts

Tables 2a and 2b indicate whether updating forecasts improves forecast accuracy. An improvement in forecast accuracy is indicated when "Backcasts" show lower forecast error scores than "Forecasts." Table 2a shows the four forecast evaluation scores for forecasts and backcasts for the revised estimate and 2b for the initial estimate. All four measures of forecast error are relatively lower for the USDA backcasts.

USDA Forecast Bias

Forecast bias is evidenced when the average of the historical forecast errors differs from zero; i.e., ME = 0. The mean errors (ME) in Tables 1a and 1b are positive and large in magnitude for all three periods except the first period in Table 1b. A positive ME indicates that the forecasts are on average too low. For example, the ME = 27.59 in Table 1a means that from 1996-2001 the USDA's forecast for the revised estimate from 1996-2001 was on average $27.59 billion too low. Given that farm sector total assets averaged over $1.1 trillion dollars over 1996-2001, this means that the USDA bias was only about 2.5 percent below average.

Does Accounting for Bias Improve USDA Forecast Accuracy?

We test whether past bias can be used to improve USDA's future predictions. Each time a new initial estimate is issued, the forecast error is updated, creating a rolling measure of the USDA's average forecast error or bias across time. Note that for this test we cannot use previously estimated bias to forecast the first year (1986), since it has no previous forecast error by which to adjust the USDA forecast. Hence the first period represents 15 bias-adjusted forecasts made from 1987-1989.

In order to better contrast the relative forecast performance of the models with and without the adjustment for bias, Tables 3a and 3b present the ratios of the forecast evaluation scores with adjustment for bias to without adjustment for bias. A ratio less than unity indicate adjusting for bias reduces error in the USDA forecasts. A ratio greater than unity indicates adjusting for bias increases error in USDA forecasts. A ratio equal to unity indicates the bias adjustment has no effect on the USDA forecast performance.

Table 3 shows the results of using the bias or average forecast error incurred in earlier period forecasts to adjust forecasts for the next estimate. Ratios greater than unity for forecasts of both the revised (Table 3a) and initial (Table 3b) estimate of farm sector total assets indicate early adjustments for bias increase forecast error in contrast to no adjustment from 1987-1989. However, in the second period (1990-1995) the ratio begins to fall below 1.0, indicating that adjusting the USDA's forecasts for previously observed bias slightly improved forecast performance. By the third period (1996-2001) the ratios are below unity and even smaller than the second period. Forecast accuracy increases as we increase the number of forecast errors used to calculate the USDA's bias-adjustment factor. The results suggest that future forecasts by the USDA may benefit by adjusting for systematic forecast error observed in earlier periods.

Forecasting the Initial Estimate: USDA versus CPI-Based Model

Table 4a contrasts USDA forecasts to CPI-based forecasts for the USDA initial estimate of total farm sector assets. USDA-I represent only the USDA first forecast for the initial estimate. These first forecasts are issued as early as January of the forecast year and no later than March. Eleven first forecasts were issued in January, one in February, and two in March. Naive-I represents the first forecast issued of the initial estimate by the naive model. The first forecast issued by the naive model for December 1988 was in March 1988 while all subsequent 13 first forecasts for each subsequent year from 1989-2001 are issued in January of the forecasted year.

The first two rows in Table 4a show that the first forecasts from the naive model outperform forecasts made by the USDA. The RMSE for the USDA-I is 56.83 whereas it is 46.28 for Naive-I. MAPE for the USDA-I model is 4.47 whereas it is only 3.70 for the Naive-I.

USDA-II represents all forecasts throughout the forecast year made prior to the December 31 date. Updates are issued as early as April and as late as December. The average update is issued about August. A total of forty forecasts, 14 first and 26 updates, were issued by the USDA from 1988-2001. Naive-II issues updated forecasts only in those years in which a newer initial estimate is made by the USDA later during the forecast year. This occurs in seven of the fourteen years. Updates are issued as early as April and as late as November, with the average update in the years with updating occurring in August. Hence a total of 21 forecasts, 14 initial and 7 updates, are issued by the naive model from 1988-2001.

The last two rows in Table 4a show that while both the USDA and the naïve model improve with the inclusion of updating forecasts, the naïve model (Naïve-II) outperforms the USDA model (USDA-II). The naïve model without any updating (Naïve I) outperforms the USDA's combined first and updated forecasts (USDA II).

Backcasting the Initial Estimate: USDA versus CPI-Based Model

Table 4b contrasts backcasts by the naive model to those issued by the USDA for the initial estimate. The naïve model outperforms the USDA forecaster for early backcasts. USDA-I and Naive-I in Table 4b show the results for backcasts made within the first quarter of the year (except for 2000 when the USDA issued its first forecast in April). The RMSE and MAPE for the USDA I forecaster are 32.24 and 2.34 percent versus the hurdle model's 30.32 and 2.23 percent.

However, when all of the backcasts issued by the USDA are compared to the all of the backcasts issued by the naive model, the USDA's backcasts are more reliable. The RMSE and MAPE for the USDA (USDA II) are 27.75 and 1.82 percent versus 30.09 and 2.27 percent for the naïve forecaster. Twenty four of the USDA's 40 backcasts (60 percent) are made after April. Only one more backcast is issued by the hurdle model after the first quarter. The addition of the more-informed, later backcasts by the USDA are the reason the evaluation scores for the USDA's over the full year (USDA-II) are superior to the hurdle model's (Hurdle II). This may reflect that the USDA is now making updated forecast based on some of the actual data which it will use to make its estimates of total farm sector assets. While the USDA manages to reduce and even eliminate the forecast gap between itself and the naïve model over time, it is not until late in the year following the forecasted date that the naïve model's superiority is overcome.

Predicting the Revised Estimate: USDA versus CPI-Based Model

Tables 5a and 5b show the same test models run on forecasts of the revised estimate. Table 5a shows the naive model outperforms the USDA both with and without updated forecasts included. RMSE and MAPE scores are considerably lower for the naive model for both the early-year forecasts as well as the full-year forecasts. Table 5b again shows the same occurs for the backcasts as well. Unlike the backcasts of the initial estimate (Table 4b), updating backcasts of the revised estimate does not improve the USDA's reliability in contrast to the naïve model. Interestingly, knowledge of some of the data used to make the USDA's initial estimate does not improve USDA forecast accuracy vis-à-vis a naïve model regarding the future revised data.

Conclusions

Based on our analysis of the USDA's forecasts of the farm sector's total assets from 1986-2002 as published in the USDA's Agricultural Outlook:

(1) USDA predictive accuracy has not improved over time

Four different statistical forecast error criterion (rmse, mae, mape, and mean error) indicate that USDA forecast accuracy did not improve from 1986-2002. Previous research has shown similar results for other private and public sector agencies' forecasts of other economic and financial variables.

(2) Updating improves USDA predictive accuracy

One test of informational efficiency is that as time progresses toward knowledge of the forecasted actual number, forecast accuracy should improve. That the USDA improves its accuracy when it updates its earlier forecasts indicates there are informational gains to USDA forecast consumers from its updating process.

(3) USDA predictions could benefit somewhat by incorporating past errors

Past research shows that measuring and incorporating past bias rarely translates into better future forecasts. However, in the case of USDA predictions of farm sector total assets, we show a reduction in future forecast error would have occurred if the USDA adjusted its predictions by the bias (mean error) in its earlier forecasts. While the reduction in forecast error was marginal, it increased over time.

(4) USDA prediction errors exceeds those of a CPI-based model

Our research showed the USDA could have improved its forecast accuracy had it accounted for inflationary expectations from 1986-2002. However, future research would be necessary to determine whether the use of inflationary expectations would have shown the same improvements in earlier periods.

Following the results presented in this paper, future forecast models of farm sector total assets might consider incorporating the information contained in inflationary expectations. The accuracy of CPI-based forecasts is a useful minimum hurdle for any economic model used to forecast nominal values. Further improvements in forecast accuracy might also be achieved through evaluating the accuracy of predictions of the six different asset categories that comprise farm sector total assets.

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Table 1a

Scores for USDA Predictions of Revised Estimates of Total Farm Assets

Period	ME	MAE	RMSE	MAPE	PREDS
1996-2001	27.59	52.04	61.65	4.5	32
1990-1995	15.44	21.26	25.64	2.36	32
1986-1989	32.35	38.53	42.90	4.95	27

Table 1b

Scores for USDA Predictions of Initial Estimates of Total Farm Assets

Period	ME	MAE	RMSE	MAPE	PREDS
1996-2001	28.63	42.94	54.52	3.71	32
1990-1995	11.70	17.89	23.39	1.98	32
1986-1989	-2.10	18.14	24.95	2.44	27

Notes:
ME: mean error
MAE: mean absolute error
RMSE: root mean squared error
MAPE: mean absolute percentage error
PREDS: number of quarterly predictions evaluated for the period

Source: *Agricultural Outlook*; Economic Research Service/U.S. Department of Agriculture.

Table 2a

Predictive Accuracy Scores for Revised Estimates of Total Farm Assets 1986-2002

	ME	MAE	RMSE	MAPE	PREDS
Backcasts	17.31	30.26	36.09	3.16	45
Forecasts	31.98	44.00	53.92	4.58	46

Table 2b

Predictive Accuracy Scores for Initial Estimate of Farm Assets 1986-2002

	ME	MAE	RMSE	MAPE	PREDS
Backcasts	6.22	17.81	26.64	1.83	45
Forecasts	20.70	35.54	46.04	3.60	46

Notes:
ME: mean error
MAE: mean absolute error
RMSE: root mean squared error
MAPE: mean absolute percentage error
PREDS: number of quarterly predictions evaluated for the period

Source: *Agricultural Outlook*; Economic Research Service/U.S. Department of Agriculture.

Table 3a

Ratios of Scores for Revised Estimates with and without Adjustment for Bias

Period	ME	MAE	RMSE	MAPE	PREDS
1996-2002	0.61	0.94	0.94	0.95	32
1990-1995	0.56	0.99	1.00	0.99	32
1987-1989	1.17	1.16	1.17	1.16	15

Table 3b

Ratios of Scores for Initial Estimates with and without Adjustment for Bias

Period	ME	MAE	RMSE	MAPE	PREDS
1996-2002	0.63	0.97	0.96	0.97	32
1990-1995	0.91	0.98	0.99	0.98	32
1987-1989	2.36	1.37	1.22	1.38	15

Notes:
ME: mean error
MAE: mean absolute error
RMSE: root mean squared error
MAPE: mean absolute percentage error
PREDS: number of quarterly predictions evaluated for the period
Ratio = score with adjustment for bias divided by score with unadjusted USDA prediction

Source: *Agricultural Outlook*; Economic Research Service/U.S. Department of Agriculture.

Table 4a

USDA and Naïve Forecasts on Revised Estimates of Total Farm Assets 1988-2002

	ME	MAE	RMSE	MAPE	PREDS
USDA - I	30.29	49.89	62.05	5.00	14
Naïve – I	24.55	37.05	46.88	3.75	14
USDA – II	32.60	45.91	55.98	4.64	39
Naïve – II	23.98	34.51	43.48	3.55	21

Table 4b

USDA and Naïve Forecasts on Initial Estimates of Total Farm Assets 1988-2002

	ME	MAE	RMSE	MAPE	PREDS
USDA - I	24.79	45.52	56.83	4.47	14
Naïve – I	19.05	37.62	46.28	3.70	14
USDA – II	25.48	38.24	48.59	3.76	39
Naïve – II	17.36	32.45	41.72	3.20	21

Note 1:
ME: mean error
MAE: mean absolute error
RMSE: root mean squared error
MAPE: mean absolute percentage error
PREDS: number of quarterly predictions evaluated for the period

Note 2
USDA I is the initial forecast issued by the US Department of Agriculture for total farm assets at the beginning of the year. USDA II represents all forecasts issued by the USDA in the year of the forecast date. Naïve I is the initial forecast issued by the CPI-adjusted model for total farm assets at the beginning of the year. Naïve II represents all forecast issued by the CPI-adjusted model in the year of the forecast date.

Source: *Agricultural Outlook*; Economic Research Service/U.S. Department of Agriculture.

Table 5a

USDA and Naïve Backcasts on Initial Estimates of Total Farm Assets 1987-2002

	ME	MAE	RMSE	MAPE	PREDS
USDA – I	8.04	23.24	32.24	2.34	15
Naïve – I	12.5	23.33	30.32	2.23	15
USDA – II	8.64	18.4	27.75	1.82	39
Naïve - II	14.29	23.84	30.09	2.27	17

Table 5b

USDA and Naïve Backcasts on Revised Estimates of Total Farm Assets 1987-2002

	ME	MAE	RMSE	MAPE	PREDS
USDA – I	16.66	35.39	41.38	3.62	15
Naïve – I	27.07	25.49	35.46	2.52	15
USDA – II	16.20	31.14	37.26	3.14	39
Naïve - II	22.57	28.29	36.05	2.81	17

Note 1
ME: mean error
MAE: mean absolute error
RMSE: root mean squared error
MAPE: mean absolute percentage error
PREDS: number of quarterly predictions evaluated for the period

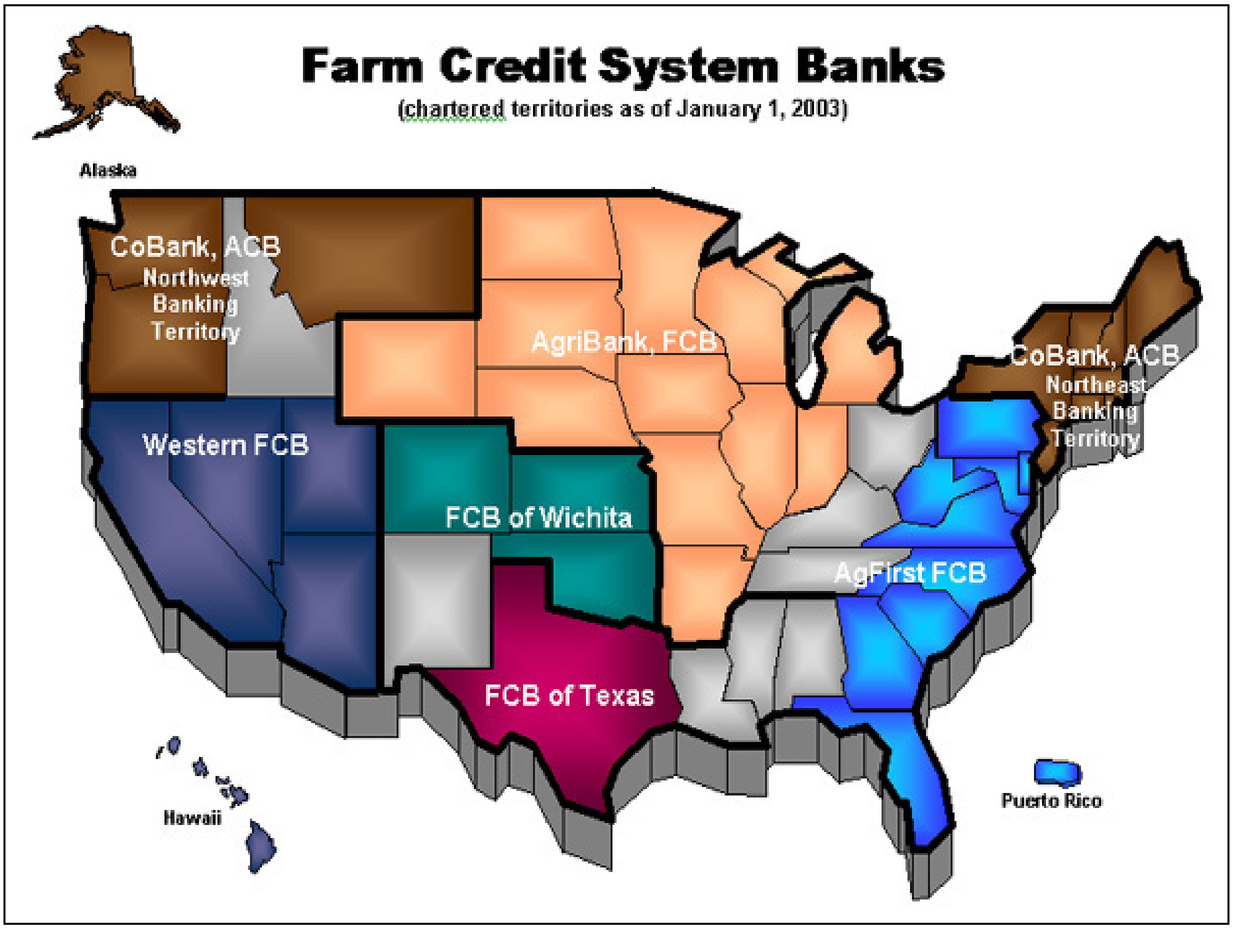
Note 2
USDA I is the initial backcast issued by the US Department of Agriculture for total farm assets at the beginning of the year following the forecast date. USDA II represents all backcasts issued by the USDA in the year following the forecast date. Naïve I is the initial backcast issued by the CPI-adjusted model for total farm assets at the beginning of the year following the forecast date. Naïve II represents all forecast issued by the CPI-adjusted model in the year following the forecast date.

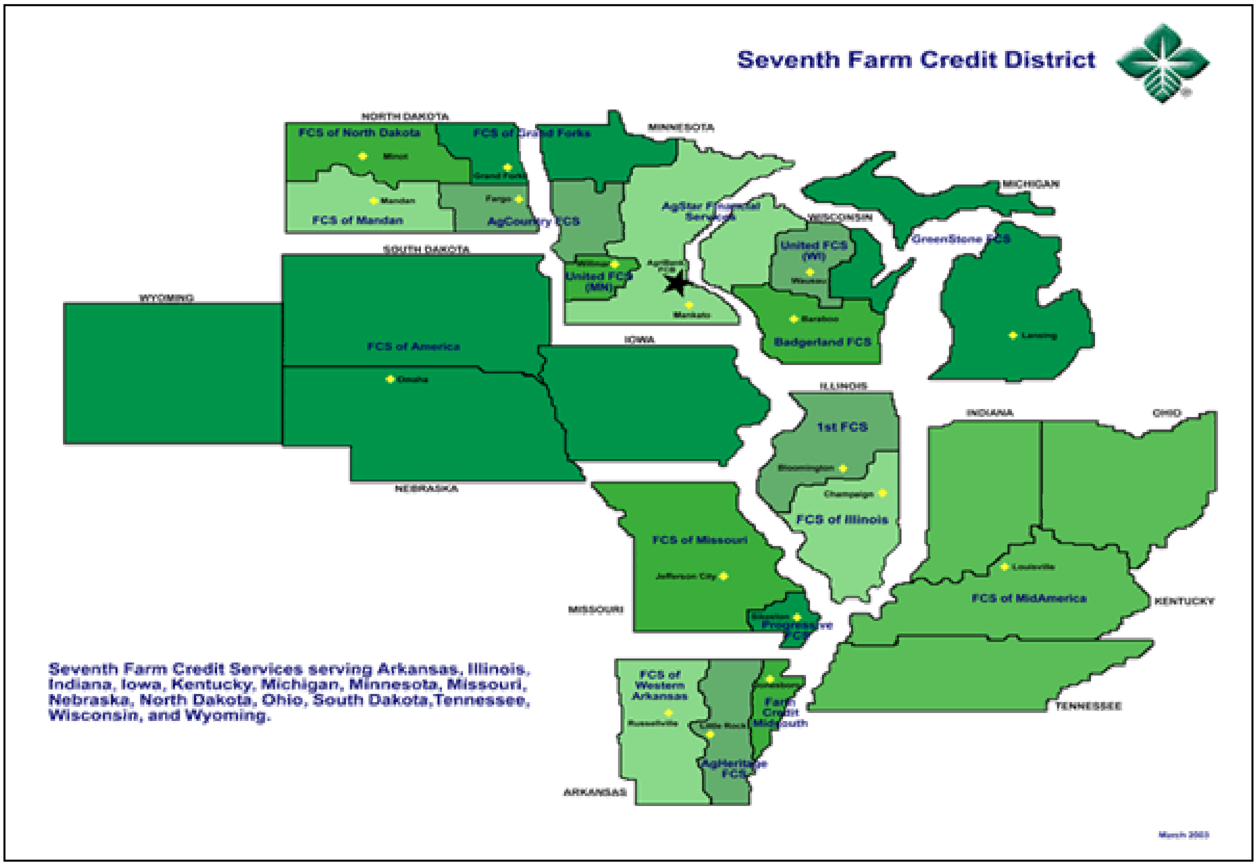
Source: *Agricultural Outlook*; Economic Research Service/U.S. Department of Agriculture.

Credit Risk Management
October 6, 2003

By
Ross Anderson
AgriBank, FCB
Vice President-Credit

Presented by Gary Mazour, Farm Credit Services of America



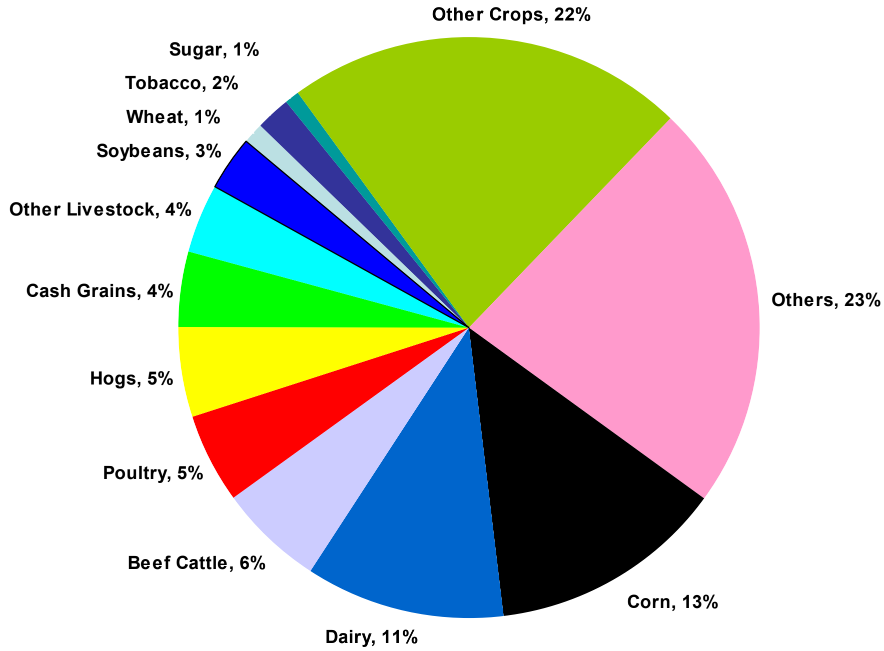


District Portfolio

(in Millions)

	1995	1996	1997	1998	1999	2000	2001	2002
Loan Volume	$13,529	$15,144	$15,876	$17,318	$17,047	$18,512	$19,949	$22,229
Adverse $	851	777	721	856	861	925	864	792
Adverse %	6.3	5.1	4.5	4.9	5.1	5.1	4.3	3.8%
Nonaccrual $	280	188	187	341	312	195	214	192
Nonaccrual %	2.1	1.2	1.2	2.0	1.8	1.1	1.1	0.9%
Nonaccrual % of Adverse Dollars	32.9	24.2	25.9	39.8	32.2	21.1	21.1	24.3

District Loan Distribution By Commodity
(As of December 31, 2002)



AgriBank Loan Portfolios
(as of December 31, 2002)

	Volume MM	% of Portfolio
Wholesale	18,365	94.8
Commercial Lending	**515**	**2.7**
Capital Markets	**323**	**1.6**
OFIs	**140**	**0.7**
RAU & NAS	**36**	**0.2**
AgriBank	19,370	100.0%

Credit Information Disclosure Today

- Accrual/nonaccrual
- Performing/nonperforming
- Restructured volume
- Type of loan—operating, IT, mortgage
- Commodity diversification
- Loan size stratifications/concentrations
- Credit quality
  - % Adverse

Disclosure Drivers Future

- Enron, WorldCom, TYCO
- Transparency:
  - AICPA SOP Allowance for losses
  - Moodys and S & P
  - Disclosure---Fannie, Freddy, SEC
  - Farm Credit System SEC?

Credit Information Disclosure

- Credit quality ----How should information be disclosed?
  - Full time, part time, commercial ?
  - By size ?
  - By primary commodity ? i.e. corn
  - By geographic area produced, or sold?
  - Allowance for losses disclosure should align with credit quality disclosure

Credit Information Disclosure

- Allowance should reflect estimated charge-off exposure in the portfolio---not forward looking.
  - Allowance information must be relevant, objective, and measurable.
  - What have been the charge-offs?
  - What criteria exists that will drive charge-offs over time?
- Charge-offs to credit risk in the portfolio
  - Today-----Uniform classification system
  - Future-----Risk rating system or other ??

Credit Information Disclosure

- Changing risk rating system
  - Each institution may have distinct rating system
  - Basel II requires less than 30% of dollars in any one risk rating category
  - Producer credits vs. commercial credits or one set of definitions
  - Current risk rating system incorporates both Probability of Default and Loss Given Default. Basel II separates the two.
  - Future----risk rating = Probability of default , not expected loss

Use of Internal Probability of Default (PD) Ratings

- Credit approval authorities and limits
- Evaluation of loan pricing
- Analysis of the Bank's capital adequacy, allowances, and profitability
- Performing stress tests to assess capital adequacy

Alternatives from Basel

- Basel 1---most assets risk weighted 100%
- Standardized Approach---some assets rated more than 100%
- Internal Ratings Based---may be used by only the very largest banks, but concepts reflect some of the most advanced thinking in risk management

Risk Weights
Standardized Approach -Corporates

Credit Assess	AAA to	A+ to A-	BBB to BB-	Below BB-	Unrate d
Risk	20%	50%	100%	150%	100%

System Risk Management Objectives:

- Develop a tool to assist in growing and managing the total loan portfolio.
- Develop a common framework to assess risk within the System.
- Establish uniform language and definitions to maximize effective communication within and among institutions in the System.
- Establish definitional compatibility with regulation for the designation of special mention and classified loans.
- Establish definitions that support agribusiness/commercial loans, as well as production loans.
- Provide a tool to improve disclosure of System credit risk to investors in System debt.

System Risk Management Objectives: (Cont):

- Establish a risk rating model that complies with the guidelines in the Basel II Accord regarding sufficient granularity.
- Establish definitions and objective criteria that are highly predictive over the business cycle and longevity of predictive power
- Establish definitions that result in grade consistency across sub-portfolios.
- Develop definitions and a model that have a low cost to administer.
- Establish that definition of probability of default is indicated by 90 days past due or nonaccrual over a one-year timeframe.

Next Steps-Risk Rating

- Obtain PPC endorsement this fall
- Provide education—video, guidebook w/100 loan examples
- Determine if loan systems have right fields, if not, modify systems to store data
- Develop and validate initial PDs by risk rating, including standard deviations
- Develop objective criteria per risk rating to drive consistency
- Develop and validate LGDs
- Implement a national "Peer Review" process to ensure consistency

			Example 6 Objective Criteria			
			Contract Swine/Broiler			
	4	5	6	7	8	9
WC/AGI						
Current Ratio	1.35:1	1.30:1	1.25:1	1.20:1	1.0:1	1.00:1
Solvency	>40%	>35%	>30%	>25%	>25%	>20%
CDRC	>150%	>140	>125%	>120%	>115%	>105%
CDRC	>20%	>20%	>17%	>15%	>12%	>10%
Margin/AGI						
Management	Very	Strong	Above	Average	Minor	Some
Character	Strong		Average		Concern	Weakness
Performance						
Trends						

Two Dimensional Risk Rating Model

- Probability of Default PD
  - One year PD
  - Minimum of 3 BPS (0.03%)
  - Average PD per grade, not a PD for each borrower
    - Bank's actual experience (based upon minimum observation period of 5 years)
    - Mapping to external data
    - Use of statistical default models

Two Dimensional Risk Rating Model

- Probability of Default PD
  - Issues
    - Do you measure PD based upon number of borrowers, loan numbers, or loan volume?
    - How big of a database do you need to be statistically reliable ?
    - How many years of data do you have?
    - What objective criteria is most useful in asset placement?
    - S & P's concerns about cycles and sufficiency of capital even w/stress testing

Two Dimensional Risk Rating Model

- Probability of Default
  A default is considered to have occurred with regard to a particular obligor when **one or more** of the following events have taken place:
  - It is determined that the obligor is unlikely to pay its debt obligations (principal, interest, or fees) in full;
  - A credit loss event associated with any obligation of the obligor, such as a charge-off, specific provision, or distressed restructuring involving the forgiveness or postponement of principal, interest, or fees;
  - The obligor is past due more than 90 days on any credit obligation; or
  - The obligor has filed for bankruptcy or similar protection from creditors.

Mapping Model

Combined System		Existing Seventh	Producer Model	Existing CoBank	RMA
1	Highest			1	1
2	Superior			2	2
3	Exceptional	1		3	3
4	Excellent	1	1	4	4
5	Strong	2	2	4 minus	4
6	Good	3	3	5	5
7	Average	3	4	5 minus	5
8	Adequate	4	5	6	6
9	Minimally Accpt.	4	6	6 minus	6
10	OAEM	5	7	7	7
11	S-Viable	6	8	8	8
12	S-Nonviable	7	8N	8	8
13	Doubtful	8	9	9	9
14	Loss	9	10	10	10

Mapping Model

Combined System 5.29	Seventh District	Moodys One-Year Default Rates	Standard and Poors	Moodys One-Year Default	Standard and Poors	Operating	Ag Mortgage AgriBank	Rural Home	Term
1		Aaa,Aa	AAA, AA	0%	0%				
2		Aa, A	AA-A	.08%	.01%				
3	1	A	A	.01%	.04%	.38%	.35%	.25%	.57%
4	2	Baa1, Baa2	BBB+ ,BBB	.12%	.02%	.67%	.67%	.42%	.80%
5	2	Baa2,Baa3	BBB, BBB-	.12%	.26%	.67	.67%	.42%	.80%
6	3	Ba1	BB+	.78%		1.25%	1.1%	1.01%	1.44
7	3	Ba2	BB+, BB	.65%	1.12%	1.25%	1.1%	1.01%	1.44 %
8	4	Ba3	BB, BB-	2.93%		5.17	3.49%	5.29%	4.09 %
9	4	Ba3, B1	BB-,	7.71%	6.06%	5.17	3.49%	5.29	4.09
10	5		CCC	13.66%	25.22%				
11	6								
12	7								
13	8								
14	9								

4-Borrowers of Excellent Quality

- Leverage very low relative to industry standards with very strong liquidity. Long history of quality earnings. Interest coverage and cash flow is strong. Strong debt capacity. Where size allows, the borrower has ready access to national or regional debt markets. Alternative financing is available at all times. Management is highly regarded and has demonstrated industry experience and expertise. These are very strong assets.
- Placement Guidance
  Rated companies in this category would include those typically rated BBB+ or BBB (S&P) or Baa1 or Baa2 (Moodys). Would typically include the highest quality agricultural production loans and local agribusiness accounts. Would include loans with Farmer Mac standby purchase commitment.

7-Borrowers of Average Quality

- Average leverage and acceptable liquidity based on peers in the industry. Adequate earnings, cash flow, and debt service. Trends are positive but may not be consistently stable. Typically operations are profitable, but losses may periodically occur due to a difficult economic environment. Borrowers have sufficient strength and financial flexibility to offset these events. These operations are somewhat vulnerable to prolonged adverse industry conditions. Readily able to refinance debt with other financial institutions on similar terms. Management and owners have unquestioned character.
- <u>Placement Guidance</u>
  Rated companies typically include those in the BB+ and BB (S&P) or Ba1 and Ba2 (Moodys) range.

9-Borrowers of Minimally Acceptable Quality

- More leveraged than peers in the industry and/or liquidity is weak or unstable. Earnings may be marginal, but cash flow, and debt service are sufficient but may be deteriorating, exhibiting signs of strain, are inconsistent or reliant on projections. Prone to deterioration in difficult economy. Limited access to alternative lenders. Heavy reliance on debt financing. Borrower may have difficulty in obtaining similar rates and terms. Performance record is usually satisfactory. Lender relationship satisfactory. Management is either unproven or less than average. Assets are acceptable but have conditions that could bring deterioration more quickly than other acceptable loans.
- <u>Placement Guidance</u>
  Loans with deteriorating trend but still with cash flow coverage. Might have temporary setbacks to profitability. Rated companies typically in the BB- and B+ (S&P) or Ba3 and B1 (Moodys) range. Would include loans guaranteed by federal agencies (FSA, etc).

Loss Given Default Definitions

- Default: Earlier of nonaccrual or 90 days past due
- Economic Loss: Principal plus interest at date of default (plus any unpaid fees less the present value of subsequent cash flows
- Discount rate: Loan rate at time of default

Loss Given Default

- Minimum of 7 years of data (either internal or external)
- Represent entire business cycle
- *Issues:*
  - *Does historical data reflect modern assets? i.e. are hog facilities today = hog facilities in 1990*
  - *Do we have accurate data on actual costs incurred?*

Two Dimensional Risk Rating Model

- Loss Given Default: LGD
  - Applied to facility/transaction, not borrower.
  - LGD needs to be analyzed at each institution as the institution's policies and procedures will impact LGD.
  - Average expected loss for each LGD grade
    - Seniority of position
    - Amount and nature of collateral
    - Loan covenants

Two Dimensional Risk Rating Model

- Loss Given Default: LGD
  - Economic costs
    - Advances
    - Charge-offs
    - Recoveries
    - Legal fees
    - Staff costs
    - Collection fees

Loss Given Default

LGD Terminology	Code	Range %	LGD %
Low Well secured	L W	0-15	**3**
Moderate Adequately secured	M A	15-25	**20**
High Marginally secured	H M	25-50	**50**
Severe Under secured	S U	50+	**75**

Loss Given Default
Grades and Characteristics

- Low   Range: 0-15%   LGD : 3%
  - Loans that have a substantial positive collateral margin
  - Loans with FSA or other guarantor with unquestioned financial strength (absent any loan servicing issues)
  - Loans to customers that may have a short term cash flow problem, but have other financial strengths

Loss Given Default
Grades and Characteristics

- Medium Range: 15-25% LGD: 20%
  - Loans where collateral is positive, but the margin is limited.
  - Loans that are secured by assets that may not be easily converted to cash, may decline in value rapidly, or may disappear.
  - Loans where the operation/asset is not typical for the region.
  - Loans where collateral is marginal and where an unsecured guarantee may exist.
  - Loans that may be positively collateralized but where a lengthy shutdown period may be required, generating operating losses that may erode the collateral margin.

Loss Given Default
Grades and Characteristics

- High Range: 25-50% LGD: 50%
  - Senior unsecured loans.
  - Loans where total legal obligation greatly exceeds the NRV of collateral.
  - Loans to entities where inventory represents work-in-process and further processing is necessary to make the assets marketable.
  - Loans where branded products represent a significant part of the inventory.
  - Loans secured by assets that represent economically obsolete technology, either in size, design, location, or utility.
  - Loans to entities where the diversion of collateral or collateral proceeds is high, possibility of fraud is high, or where commodities are traded and internal controls are limited.

Loss Given Default
Grades and Characteristics

- Severe Range: >50% LGD: 75%
  - Unsecured loans that are legally and contractually subordinated to other facilities.
  - Loans on special purpose facilities.
  - Loans to entities funding accounts receivable with characteristics in terms of size, location, and state laws that make the collection uneconomic.
  - Loans on assets where regulatory problems exist (EPA, DNR, USDA) which may restrict the sale or use of the asset.
  - Loans secured by legal documents that are deficient or not perfected.

Two Dimensional
Risk Rating Model

- Exposure at Default ED
  - 100% of drawn plus 75% of undrawn commitments
  - 100% of direct credit substitutes such as letters of credit or guarantees
  - 20% of short-term self-liquidating trade-related exposures such as documentary credits

Two Dimensional Risk Rating Model

- Maturity: M
  - Under foundation approach, all loans are assumed to have an average maturity of 3 years
  - Under IRB approach, the greater of 1 year or:
    - Nominal maturity of the instrument
    - Weighted maturity of the remaining contractual principal payments
    - Cap of 7 years

Retail Exposure Characteristics

- Specific product types
- Loan to person or persons
- Large pool of loans
- Each individual exposure has low value
- What loans in our portfolios are “Retail?”

Recovery Rates

- Operating
- IT
- Scorecard
- Mortgage ≥50% L/AV
- Mortgage <50% L/AV
- Rural Home

Primary Issues

- Change…. lender mind set =
  - Today
    - RR = PD * LGD
  - Future
    - RR = PD
    - Loss = LGD
    - Expected loss = PD * LGD
- Do I have to risk rate more loans?
- 14 vs. 10 categories
- Best producer loans are not A1s
- Combining producer and capital market loans into one grid
- Placement of FSA guarantees
- Placement of Farmer Mac stand-bys
- Consistency of implementation

Multi-State Efforts to Evaluate Alternative Farm Savings Account Programs

Presented by Brent Gloy*
Cornell University
Annual Meeting of NCT-194
10-6-03

*This work is the product of a number of individuals

Background: The People

- Collaborators:
  - Economic Research Service – Durst, Dismukes, Monke
  - Kansas State –Williams, Schurle, Langemeier
  - North Dakota State –Swenson
  - Illinois – Ellinger, Schnitkey
  - Cornell – LaDue, Gloy
  - Please forgive any omission of other collaborators at these institutions
- Funding and guidance -- RMA

The Task

- Objectives:
  - Estimate farm income variability and assess producers' abilities to accumulate and use savings for risk management
  - Provide a risk management tool that will assist farmers in making decisions about savings, including the use of subsidized savings accounts

Savings Accounts

- Idea has appeal – encourage farmers to save when times are good
- Assist farmers in managing revenue risk
- The amount and type of encouragement varies
  - Tax deferral
  - Government matching
  - Both
- Various implementation schemes
  - All based on tax measures of income

Savings Accounts

- Subsidy component of programs differs
- Policy aimed at market failure?
  - Is savings constrained? Do farmers systematically under-save?
  - I don’t know
  - If these (and most other) programs are evaluated in this context they probably perform poorly
- Can/should we ask/insist that farmers to save the assistance that the government provides them in good times?
  - These programs provide incentives to do this

Savings Accounts

- Problem: We know relatively little about the extent/magnitude of variation annual farm income at the farm level
- Problem: We know relatively little about the extent to which savings accounts might impact this situation

Savings Accounts Precedent: Canada's NISA Program

- Deposits based on net value of production
  - Farmer deposits were not tax deductible
  - Matched deposits
- Withdrawn when net income falls below 5 year average or when income falls below a minimum level ($20,000)
- Results:
  - Substantial balances
  - Farmers negotiated ad hoc assistance in bad times
  - NISA being revised/modified

Source: Presentation given by Greg Strain, Agriculture and Agri-Food Canada, at the Farm Savings Accounts and the Farm Safety Net Workshop, Washington, D.C. June 2, 2003

Savings Accounts Precedent: Australia's Farm Management Deposits

- Tax deferral incentive
  - Cannot make taxable <u>farm</u> income negative
  - Cannot build balance in excess of 300,000AUD
  - Cannot be used as collateral
  - Provided some "exceptional circumstance" withdrawals, i.e., put the money in and take off your taxes, take it out tax free
  - About 10% of farms utilize

Source: Presentation given by Trish Gleeson, Principal Economist Agricultural Commodities, abareconomics, at the Farm Savings Accounts and the Farm Safety Net Workshop, Washington, D.C. June 2, 2003

The Programs

1. Farm and Ranch Risk Management (FARRM) Accounts
   - Recent support for the idea
   - Tax deferral incentives
2. Counter-Cyclical Accounts
   - Recent support
   - Direct government support program
3. Individual Risk Management Accounts (IRMA)
   - Alternative savings account program
   - Blends aspects of CC and FARRM

Details: FARRM Accounts

- Eligibility: positive net income
- Deposits: 20% of net income
- Income tax on deposits is deferred, earnings on deposits are taxable
- Considered two types of withdrawal rules:
  - Not specified in proposed program – conducted some analyses on movement within tax brackets
  - This benefit appears to be modest in NY (Cornell)
- Basic analyses examined withdrawals
  - If gross income falls below 90% of 5 year average,

  $\text{withdrawal}_i = \min(\text{balance}_i, 90\%*5\text{yrAve} - \text{income}_i)$
  - Used same rules for all three types of accounts

Details: CC Accounts

- Eligibility: 5 year average gross income over $50,000
- Deposits: 2% of gross income, up to $5,000 plus government match
- Only earnings on deposits are tax deferred
- Basic analyses examined withdrawals
  - If gross income falls below 90% of 5 year average,

  $withdrawal_i = \min(balance_i, 90\% * 5yrAve - income_i)$

IRMA: The General Idea

- Place crop insurance premiums in a tax-deferred interest bearing account
- Instead of subsidizing crop insurance premiums, USDA matches the producer's contribution
- Generates a whole-farm revenue insurance plan rather than commodity by commodity insurance

Details: IRMA

- Eligibility: Positive net income
- Deposits: 2% of gross income, with a high income kicker
  - If income > 110% of 5 year average, contribute 25% of the gross income amount over 110%

  Government Match of 2% of gross farm revenue (likely high)

  Maximum cumulative balance is 150% of 3 year average gross revenue
- Income tax on deposits and earnings are deferred
- Basic analyses examined withdrawals
  - If gross income falls below 90% of 5 year average,

  $withdrawal_i = \min(balance_i, 90\%*5yrAve - income_i)$

Background: Method and Data

- Partner institutions use farm record data to develop comparable panel data sets
  - Begin with records for 1997 to 2001
  - Each institution needed to standardize the records
  - Provide variability with respect to enterprise and geographic region
  - ERS to use IRS data

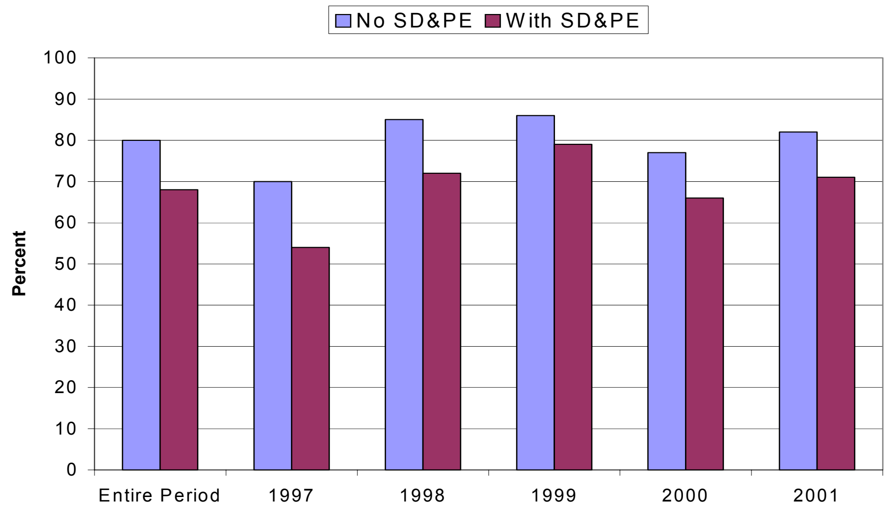
Background: Method and Data

- Proposed programs based primarily on tax records so each institution was required to develop measure that correspond to taxes
- Developed a standard approach for evaluating each program and measures of variability
- Each institution summarized the basic aspects of this data

Tasks

- Analysis begins with basic questions
  - Income variability
  - Eligibility
  - Basic withdrawal rules
- Expanded analysis will examine
  - “Behavioral” based rules
  - Cash flow and financial situation considerations

NY Farms with Positive Tax Liability



Preliminary Results
Illinois, Kansas, New York, North Dakota

Paul Ellinger, Brent Gloy,
Andrew Swenson, Jeffery R. Williams

Research Stages

- Phase I – ERS/RMA
  - Measure the variability of farms with farm records panel data
  - Estimate the impact of 3 alternative proposals
  - Identify issues
- Phase II – ERS/RMA
  - Risk management tool
- Phase III and beyond – research group
  - Customized – hybrid program
  - Evaluate savings tools in combination w/risk management tools (ex. Crop insurance)
  - Accounting issues related to farm variability
  - Consideration of financial condition
  - Behavioral cash rules

General Program Design

- Establish criteria for depositing funds and withdrawing funds.
  - Typically, current year income (net or gross) relative to historical average
- Benefits to producers are typically tax deferral and governmental match

Research Issues

- Previous research suggests benefits to size
- Measures of variability
  - net v gross
  - cash v accrual
- Moving average calculations
- Time frame
- Changes in farm size and structure
- Producer withdrawals
- Cash flow issues
- Data discrepancies

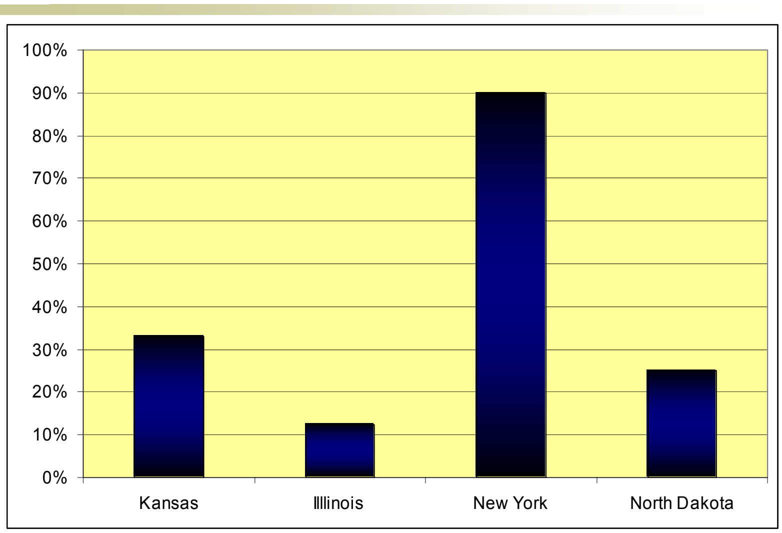
Output Tables

- Descriptive statistics
- CDFs of variability relative to min and max
- Deposit and withdrawal patterns by size of farm
  - FAARM accounts
  - Counter-cyclical
  - IRMA
- Sensitivity analysis to withdrawal rules

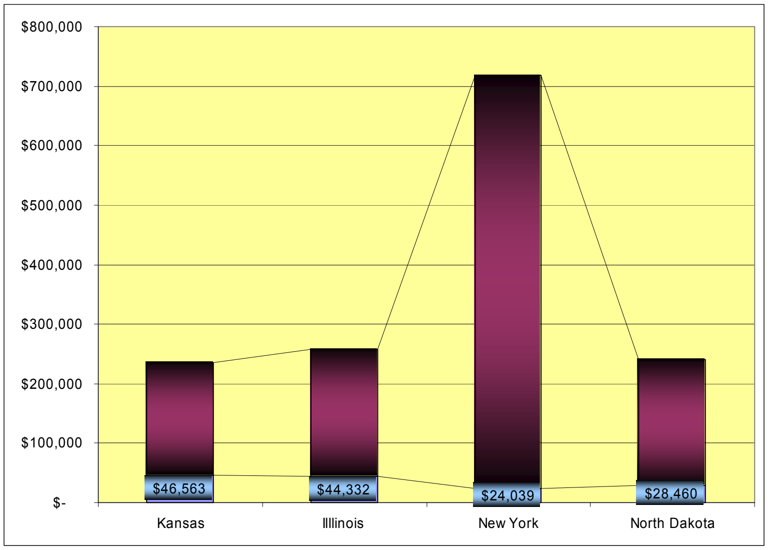
Descriptive Data

		Kansas	Illinois	New York	North Dakota
Number of farms		699	1,716	142	258
Average Gross Income (1997)		$ 235,725	$ 256,811	$ 718,675	$ 239,764
Average Gross Income (2001)		227,434	262,482	1,081,018	315,127
% Gross Income from Livestock (1997)		34.30%	15.80%	over 90%	24.00%
% Gross Income from Livestock (2001)		32.90%	12.30%	over 90%	25.00%
Average Net Income (1997)		$ 46,563	$ 44,332	$ 24,039	$ 28,460
Average Net Income (2001)		32,632	36,668	64,353	42,725
Distribution of Farms (2001)					
Gross Income					
	Less than $100,000	29%	25%	29%	9%
	$100,000 - 250,000	40%	45%	40%	39%
	Greater than $250,000	31%	30%	31%	52%
Proportion of Gross Income From Livestock					
	Less than 25%	52%	83%	52%	65%
	25% to 50%	18%	6%	18%	10%
	50% to 75%	14%	7%	14%	9%
	Greater than 75%	17%	5%	17%	16%
Net Income					
	less than $0	21%	17%	21%	12%
	1 to $50,000	53%	61%	53%	57%
	Greater than $50,000	26%	22%	26%	31%

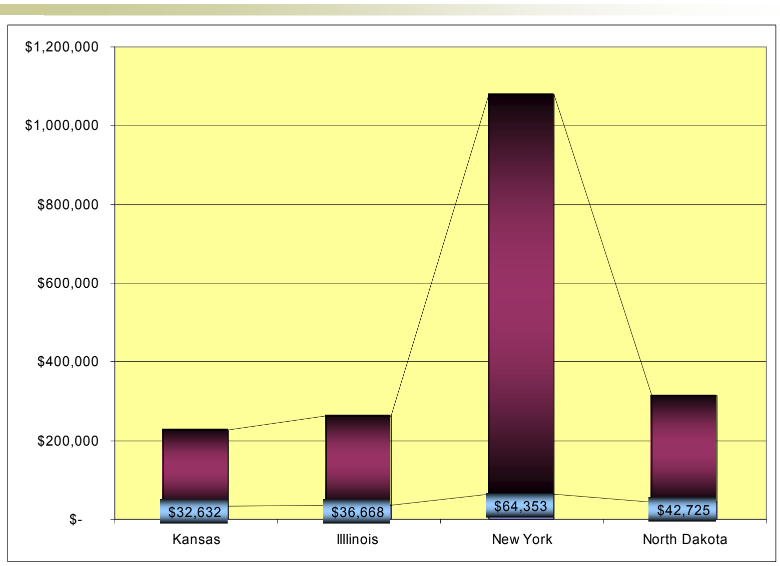
Revenue From Livestock



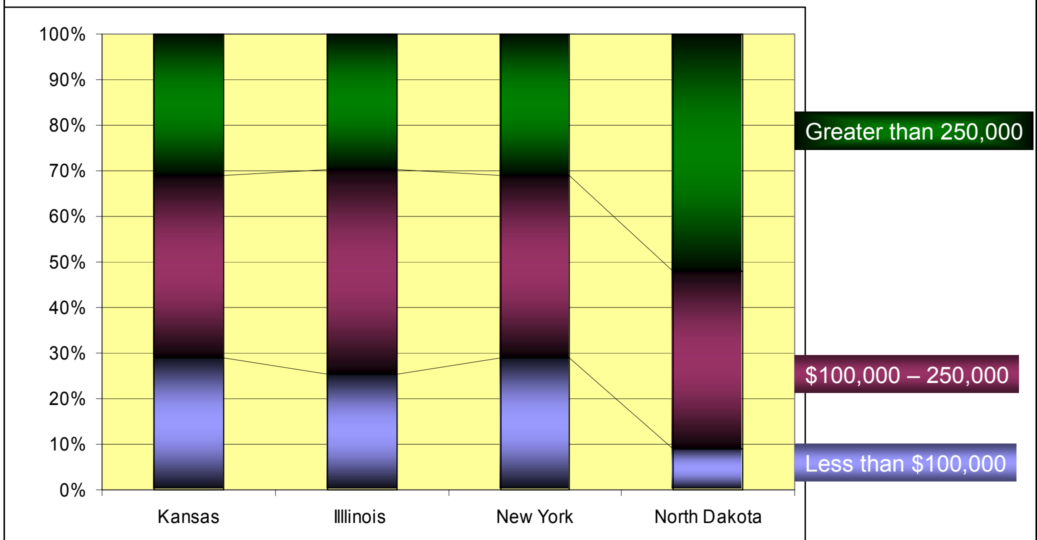
Gross Revenue and Net Farm Income, 1997



Gross Revenue and Net Farm Income, 2001

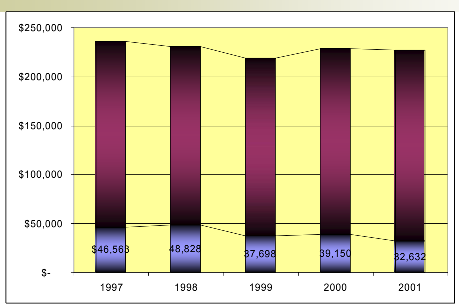


Farm Size Distribution

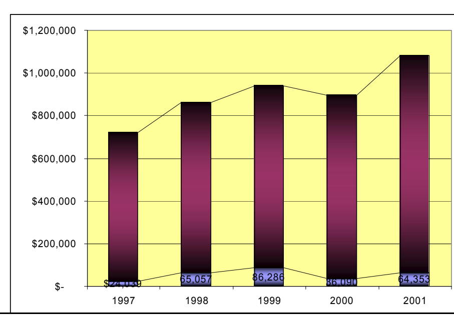


Average Revenue and Net Income

Kansas



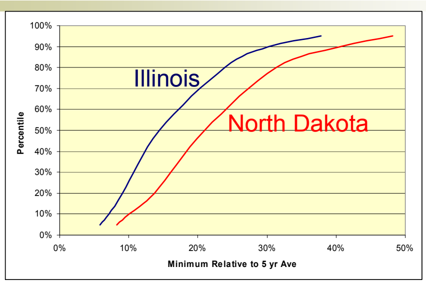
New York

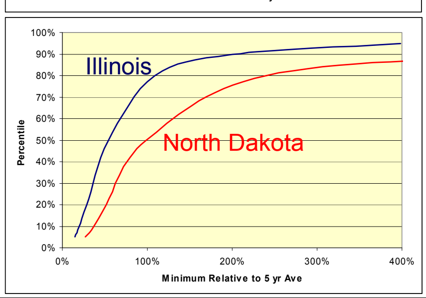


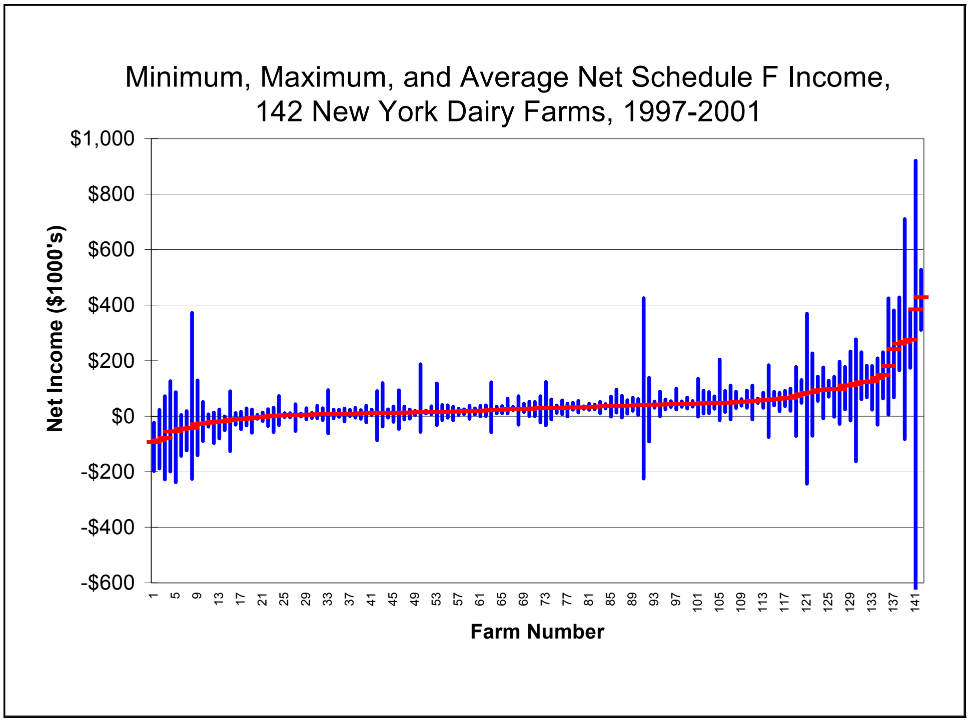
Income Descriptive Statistics

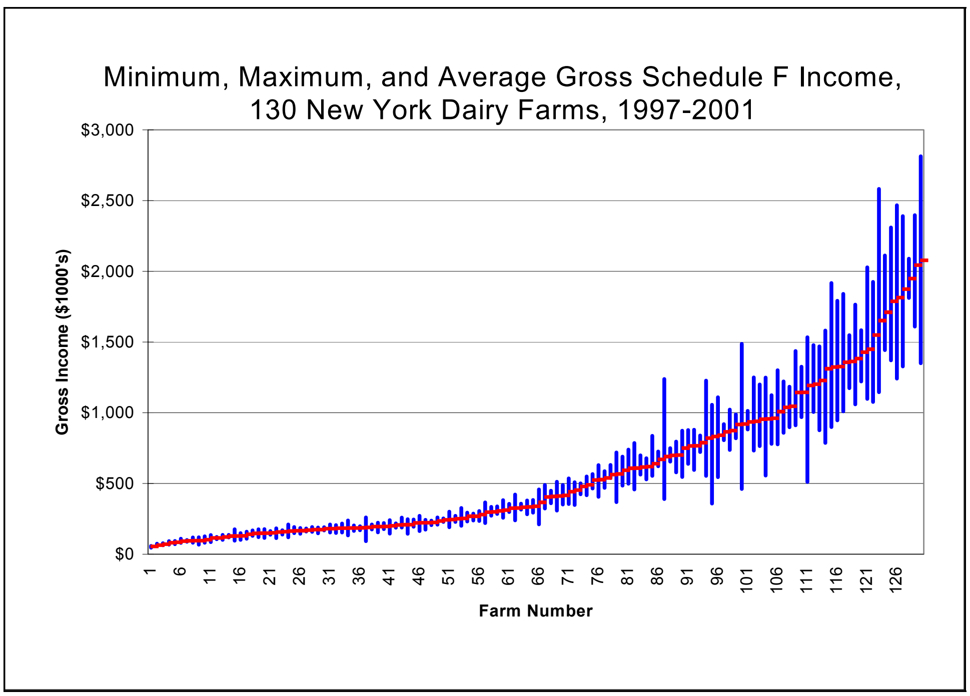
	Gross Income	Net profit/loss	Gross Income	Net profit/loss
	Illinois		New York	
Average				
1997	$ 256,811	$ 44,332	$ 718,675	$ 24,039
1998	237,558	35,526	862,279	65,057
1999	245,035	38,528	940,063	86,286
2000	256,006	38,638	894,245	36,090
2001	262,482	36,668	1,081,018	64,353
Proportion With Low Year In				
1997	16%	15%	87%	49%
1998	28%	24%	1%	9%
1999	22%	18%	1%	6%
2000	15%	17%	8%	19%
2001	18%	25%	2%	16%
Proportion With High Year In				
1997	34%	31%	1%	3%
1998	9%	15%	7%	23%
1999	12%	18%	20%	42%
2000	17%	18%	1%	8%
2001	28%	18%	70%	23%

Minimum relative to 5-year average



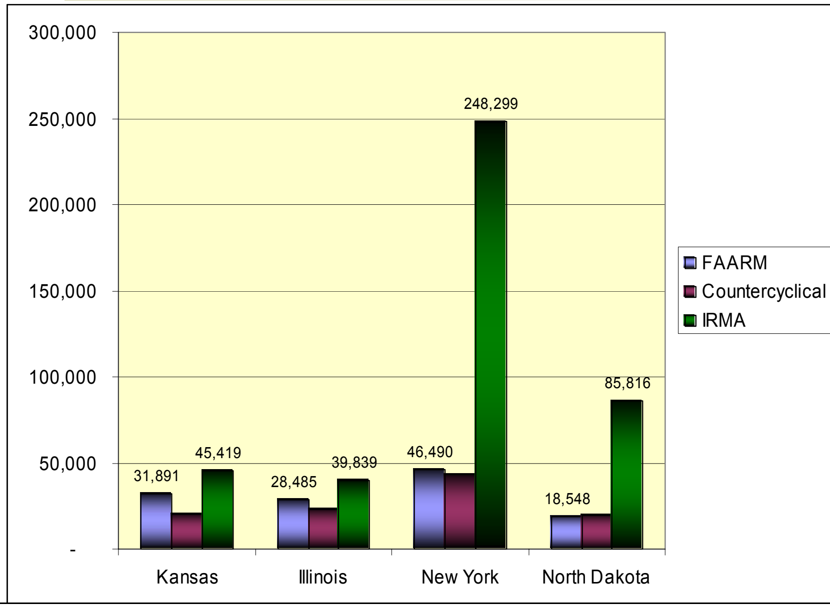



Minimum, Maximum, and Average Net Schedule F Income,
142 New York Dairy Farms, 1997-2001
Net Income ($1000's)
$1,000
$800
$600
$400
$200
$0
-$200
-$400
-$600
Farm Number


Minimum, Maximum, and Average Gross Schedule F Income,
130 New York Dairy Farms, 1997-2001
Gross Income ($1000's)
$3,000
$2,500
$2,000
$1,500
$1,000
$500
$0
Farm Number

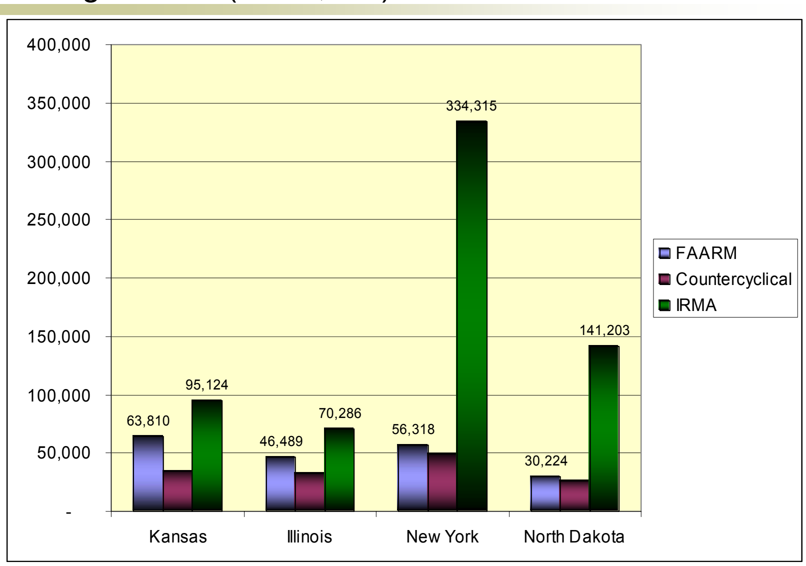
Average Ending Account Balances

All Farms



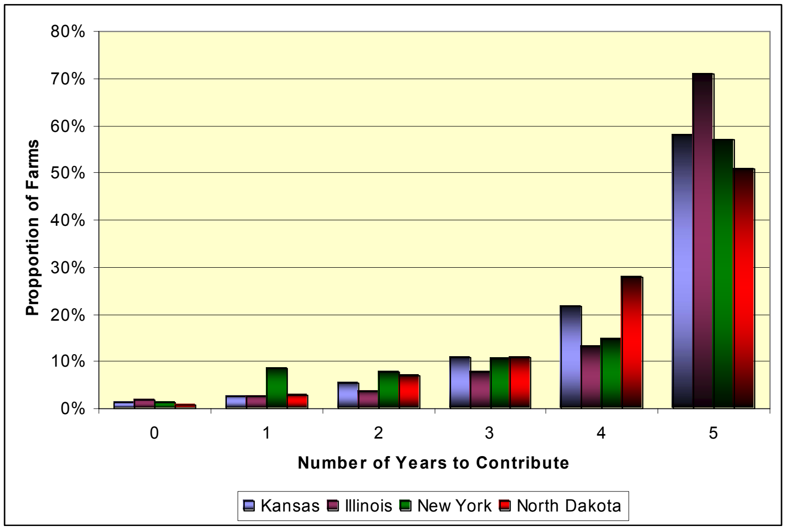
Average Ending Account Balances

Large Farms (> 250,000)



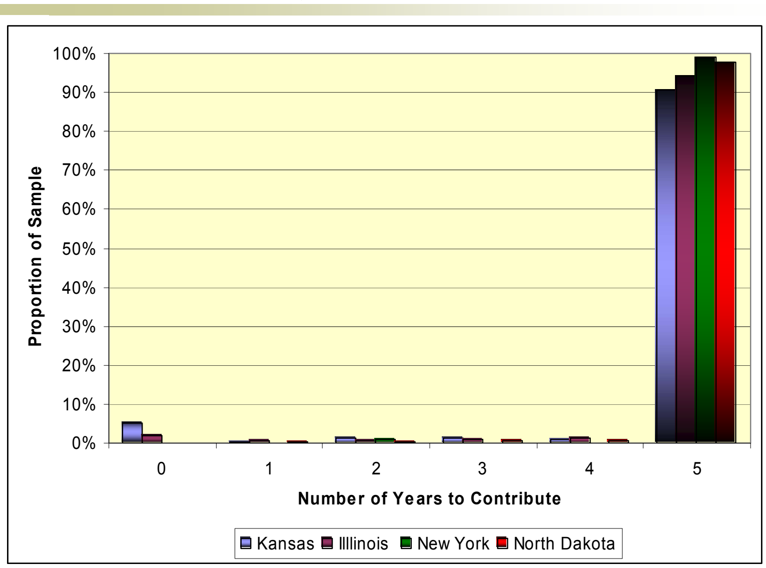
Farms Eligible to Contribute FAARM

Positive income



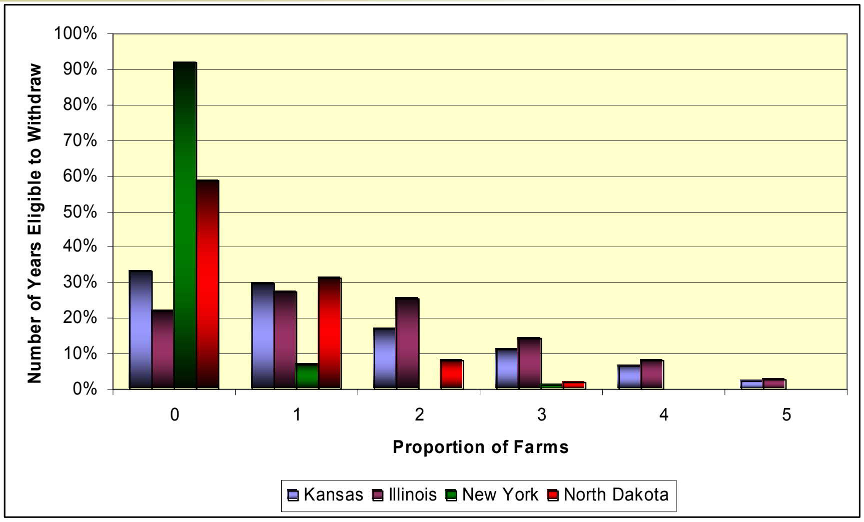
Farms Eligible to Contribute FAARM

Gross Revenue > 50,000



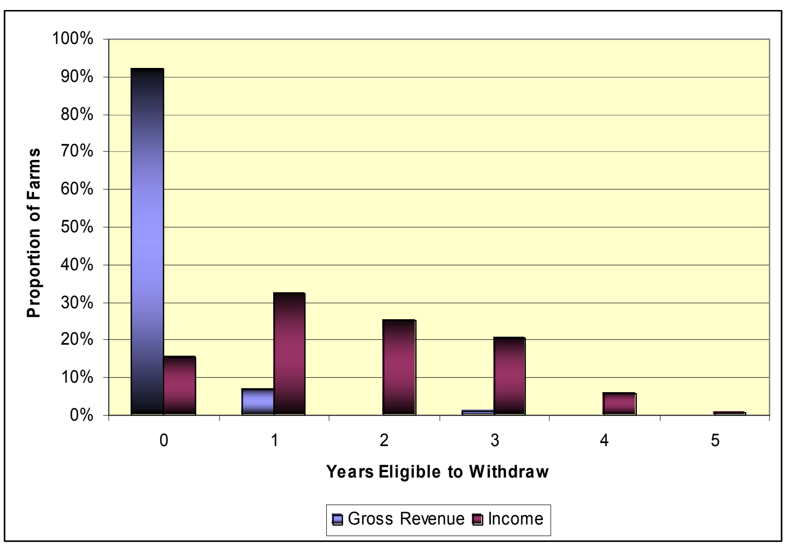
Farms Eligible to Withdraw

90% Gross Revenue



Withdrawal Rules: Gross v Net

New York

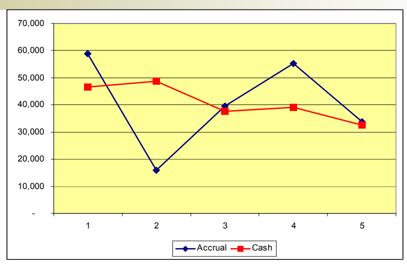


Cash v Accrual

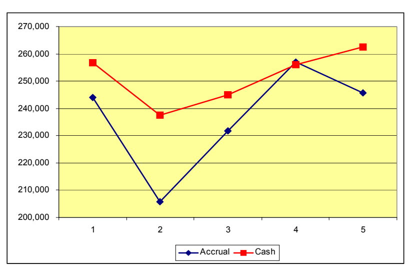
	Net Farm Income		Gross Income	
	Accrual	Cash	Accrual	Cash
1997	58,837	46,563	243,918	256,811
1998	15,934	48,828	205,889	237,558
1999	39,537	37,698	231,704	245,035
2000	55,225	39,150	257,050	256,006
2001	33,721	32,632	245,672	262,482
Average	40,651	40,974	236,847	251,578
Std Dev	17,345	6,644	19,499	10,066
CV	0.43	0.16	0.08	0.04

Cash v Accrual

Net Income



Gross Revenue



5 Year
Variability below average by growth
Illinois Grain Farms Only

Income Threshold 80%

	At least 1 year	1 in 5 years	2 in 5 years
Negative Growth	49.6%	35.5%	10.1%
Low Growth	25.8%	21.6%	3.4%
Positive Growth	38.6%	29.9%	7.6%

5 Year
Variability above average by growth
Illinois Grain Farms Only

Income Threshold 120%

	At least 1 year	1 in 5 years	2 in 5 years
Negative Growth	42.0%	35.9%	5.4%
Low Growth	29.9%	25.9%	3.5%
Positive Growth	55.9%	38.6%	14.6%

IRS Data: 2000

- Landlords
- Farm partnerships
- Subchapter S corps
- Sole proprietors (1.8 million returns)

Crop Insurance	Salaries	Self Employment Taxes
Government payments	Dividend Income	Education Credits
Depreciation	Capital Gains/Losses	Medical Credits
Mortgage Interest	IRA Contributions	Tax brackets
Gross & Net Income	Keough Contributions	
	Adjusted Gross Income	

Summary

- Report of baseline analysis: Phase I
- Sensitivity to deposit / withdrawal rules
- Issues
  - What are the incentives?
  - Accounting for changes in size and structure
  - Deposits: adequate cash flow
  - Gross revenue or net

OTHER A.E.M. RESEARCH BULLETINS

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