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Preface

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

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

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

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

Manuscripts will be accepted at any time.

Calum G. Turvey
Editor

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Associate Editor

Customer Segmentation Perceptions of Farm Credit Associations

Brian C. Briggeman and Philip Kenkel

Abstract

In 2006, the Farm Credit System released a report about the general economic and financial needs of rural America entitled HORIZONS. The objective of this study is to build on the HORIZONS project by exploring the opinions of seven Oklahoma Farm Credit Associations' senior officials and loan officers on the financial characteristics of different borrower types, their associations' competitive advantage in attracting and retaining these borrowers, and the potential loan volume growth for each borrower type. The results of this research show that senior officials are more positive than are loan officers about the financial characteristics of nontraditional borrowers. However, both groups agree that these borrowers provide the best opportunity for loan volume growth.

Key words: Farm Credit System, loan growth, market segmentation

The customer base for banks in U.S. rural markets has become increasingly heterogeneous. Farm households have evolved to a point where an operator and spouse both working on the farm represent the minority. Small family farms own 70% of the land but account for only 27% of U.S. production values; they receive 90% of their income from off-farm sources while commercial farms receive only 30% from nonfarm sources (Hoppe and Banker, 2006).

In addition to this evolution, the financial needs of U.S. agricultural borrowers have also changed. In response to these changes, rural lenders are using market segmentation techniques to improve their understanding of their current customer base, and to design strategies to effectively compete in the lending market (U.S. Department of Agriculture/Economic Research Service, 1997).

Biggadike (1981) states that market segmentation is marketing's most important contribution to strategic management. Many large and small agricultural-based businesses use market segmentation to enable more informative strategic discussions. More specifically, segmenting a market into subgroups that are homogeneous is beneficial because these subgroups are likely to behave in a similar manner. For example, Gloy and Akridge (1999) and Alexander, Wilson, and Foley (2005) each identified homogeneous groups of commercial producers to bring about more informative retail agribusiness marketing discussions and development.

Market segmentation can also be applied to the credit industry. Machauer and Morgner (2001) identified clusters of bank

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Review coordinated by Calum G. Turvey.

customers based on their needs, and from those clusters, developed a strategic matrix to inform a bank's differentiated marketing strategy with respect to information services and service distribution. In general, discussions on the strategic direction of a firm benefit from market segmentation because this serves to keep the discussion focused on what the customer needs and wants. Given the increasing heterogeneity in rural lender markets, rural lenders would be wise to define their changing lending market.

The Farm Credit System (FCS), which is a government-sponsored enterprise of borrower-owned cooperative lending institutions in the United States, recognized the need for defining its evolving credit market. To meet this need, the FCS developed a forward-looking research initiative called HORIZONS. The HORIZONS project's objective was to assess the rapidly changing financial needs of rural America. The report identifies four areas having financial needs: (*a*) producers and rural entrepreneurs; (*b*) processing, marketing, and agricultural related businesses; (*c*) rural economic development; and (*d*) rural residents.

In addition to these areas, the HORIZONS project provides a broad overview of the trends in U.S. agriculture similar to Hoppe and Banker (2006). While the HORIZONS project lays the groundwork for market segmentation, the report does not explicitly recommend a market segmentation strategy. Such strategies would presumably be developed by individual FCS associations and would be tailored to the unique characteristics of their specific customer bases.

The objective of this study is to build on the HORIZONS project by exploring the perceptions of the financial characteristics and the potential loan volume growth of different borrower types within the seven Oklahoma Farm Credit Associations (OFCAs) and their associations' competitive advantage in attracting and retaining these borrowers. Via survey responses, these perceptions are explored for senior managers and board members who set the strategic direction and for loan officers who implement those strategies and have day-to-day contact with borrowers. Integrating this information gathered from different areas of the organization could enhance a lender's ability to more effectively develop strategies to compete within a lending segment and to improve the profitability of all segments by changing marketing approaches.

Results from the survey indicate that the senior managers' and board members' perceptions do not always coincide relative to the proposed three borrower types: (*a*) full-time farmer or majority of time spent on the farm, (*b*) part-time farmer who also works off-farm, and (*c*) lifestyle farmer/landowner. This lack of consensus may be attributed to loan officers basing their perceptions on interactions with specific borrowers while senior managers and board members, referred to hereafter as senior officials, are more focused on farm sector trends.

This study provides valuable insights into how FCS associations can formulate and implement market segmentation strategies. Other rural lenders could also benefit from this study. In the section below, we continue our discussion of market segmentation for agricultural lenders. The data and methods are then presented, followed by a section devoted to the survey results. Concluding remarks are provided in the final section.

Market Segmentation for Agricultural Lenders

The central purpose of market segmentation is to identify groups of customers with similar needs and purchasing behavior. Market segmentation allows lenders to redesign their bundle of products and services and to focus their effort on market segments where they have the greatest competitive advantage. Dodson and Koenig (2004) used a national survey to examine rural market segmentation for FCS and commercial banks. They found that full-time farmers with greater than $250,000 gross farm sales tend to borrow from FCS while part-time farmers tend to borrow from commercial banks. Boehlje (1998) reports other general segmentation strategies (such as geographic location, psychometrics, and credit risk) and their implications for lenders.

Blank (2005) categorizes farmers into three distinct segments: (*a*) full-time or majority-time farmer, (*b*) part-time farmer who also works off-farm, and (*c*) lifestyle farmer/ landowner. These farmer segments are similar to the areas and trends discussed in the HORIZONS report, and they serve as the basis for the borrower types used in the survey described here. As will be argued later, these segments are easily identifiable and acted upon from a strategy perspective.

Market segmentation can be accomplished through both a "top-down" and a "bottom-up" approach. The top-down approach starts with the overall market and divides it into segments based on identifiable characteristics such as geographic or demographic characteristics (Day, 1981). The process of top-down segmentation is often incorporated into the strategic planning process, which involves higher level officials.

Market segmentation can also be achieved through a bottom-up approach. The bottom-up approach analyzes individual customer information in order to identify clusters of customers with similar demographic, behavioral, or psychographic profiles (McKenna, 1988; Pine, 1993). Bottom-up segmentation often involves operational-level personnel using databases or customer relationship management (CRM) software.

CRM is the practice of managing customer relationships through storing, collecting, and analyzing customer demographic and sales data. Many large corporations implement CRM through sophisticated systems that are both automated and expensive. Implementing CRM involves a continuing cycle of activities: targeting and marketing to customers, generating sales, developing superior experience, and developing retention and customer win-back strategies (Rigby and Ledingham, 2004).

Some associations within the FCS already implement CRM strategies. For example, Farm Credit Services of Mid-America employs a market segmentation strategy through its version of CRM, using a popular sales contact management software called ACT! to maintain its large database. Martens and Akridge (2006) provide a detailed case study of how this $8.5 billion FCS Association manages a very large area and diverse customer base. Most FCS Associations are not this large and may not have the infrastructure in place to implement an extensive CRM system. However, these smaller associations can combine the knowledge of their senior officials and loan officers to develop market segmentation strategies for building market share and retaining existing borrowers. The survey conducted in this study highlights some issues these associations should consider.

Data and Methods

The survey sample for this study consisted of loan officers and senior officials with the seven Oklahoma Farm Credit Associations (OFCAs). In 2006, these OFCAs had a total asset base of just over $1 billion (AgPreference, ACA $130.3 million; Chisholm Trail Farm Credit, ACA $185.4 million; FC of Central Oklahoma, ACA $79.5 million; FC of Enid, ACA $123.3 million; FC of Western Oklahoma, ACA $233.1 million; FCS of East Central Oklahoma, ACA $389.5 million; and FLBA of Ponca City, FLCA $47.6 million). Thus, the seven OFCAs surveyed consist of associations ranging from small to medium size in terms of total assets.

All senior officials and loan officers affiliated with the seven OFCAs were either mailed the survey or sent an e-mail containing a web link for an internet survey. Of a possible 120 surveys, a total of 54 were returned. Of those surveys returned, three were incomplete and not usable, yielding a final response rate for our analysis of 43%.

All senior officials and loan officers surveyed were asked about their opinions of important factors in attracting and retaining loans and their perceptions of the three different borrower types: (*a*) full-time farmer or majority of time spent on the farm, (*b*) part-time farmer who also works off-farm, and (*c*) lifestyle farmer/ landowner. These categories are consistent with the farmer segments suggested by Blank (2005) and implied by the HORIZONS project. These segments are also very practical since a loan officer can ascertain, with a few simple questions, in what group a potential new borrower belongs. Each survey respondent then answered choice and Likert-scale questions regarding each borrower type's financial characteristics, Farm Credit's competitiveness in obtaining new loans from each type, the loyalty of each group, projected loan growth or reduction in the next three years, and general important factors in obtaining and retaining loans.

From this survey, the different perceptions of the aforementioned characteristics and the potential loan volume growth of different borrower types held by senior officials (those who set the strategic direction) are compared to perceptions held by loan officers (those who implement the strategy). Given that the senior officials and the loan officers are exposed to the same FCS reports (namely HORIZONS) and general information from other media sources, the first general hypothesis we test is as follows:

- H_1: *Senior officials' and loan officers' perceptions of each borrower type do not differ.*

The first set of perceptions to be tested for H_1 pertain to important factors in obtaining new loans relative to each borrower type: interest rate, Farm Credit's reputation, and its lending relationship. The next perception is the competitiveness of Farm Credit in obtaining new loans from each borrower type. The final set of perceptions consists of the individual characteristics of each borrower type: repayment ability, solvency, loyalty, and expected loan volume growth. These tests of H_1 will inform the market segmentation strategy below by highlighting similar and differing opinions of those who set the strategic direction and those who implement that strategy.

To test if there is a statistical difference between senior officials' and loan officers' perceptions, a tie-corrected Kruskal-Wallis nonparametric ANOVA analysis is conducted. Following Siegel and Castellan (1988), this test is analogous to a one-way ANOVA of the medians and is asymptotically chi-squared distributed. Given our data, this nonparametric test is most appropriate because Likert-based scales are used to assess the perceptions of senior officials and loan officers.

Loan volume growth by borrower type is calculated next. The expected loan volume growth or reduction of each borrower type over the next three years is obtained with a simple histogram analysis. Survey respondents were asked to mark a box that corresponded with their opinion regarding the amount of loan growth each borrower type presented to their market over the next three years. The choices were as follows: less than –25%, –20%, –15%, –10%, –5%, 0%, 5%, 10%, 15%, 20%, and greater than 25%.

From these data, the average loan volume growth for each borrower type is calculated, standard deviations are numerically bootstrapped, and the following hypothesis is tested:

- H_2: *Expected loan volume growth for each borrower type is not different.*

Testing this hypothesis (H_2) will indicate whether expected loan growth for all OFCA respondents is equal across the different

Table 1. Loan Officers and Senior Officials in Oklahoma Farm Credit Associations: Years of Experience and Opinions Regarding New Loans

Description		Mean	Minimum	Median	Maximum	Kruskal-Wallis Test
Years with Farm Credit Association						
Loan Officers (N = 27)		13.30	1.00	11.00	35.00	0.21
Senior Officials (N = 24)		14.29	1.00	15.00	38.00	
How important is each factor in obtaining a new loan?[a]						
Interest Rate	Loan Officers	8.56	2.00	9.00	10.00	0.51
	Senior Officials	9.13	8.00	9.00	10.00	
FCA's Reputation	Loan Officers	6.78	4.00	6.00	10.00	3.50*
	Senior Officials	7.63	5.00	7.00	10.00	
Lending Relationship	Loan Officers	7.96	2.00	9.00	10.00	0.11
	Senior Officials	7.58	1.00	9.00	10.00	

Note: A single asterisk (*) denotes statistical significance at the 10% level.
[a] N = 51 total respondents, with answers on a scale from 1 to 10 (1 = not important; 10 = very important).

market segments. In other words, does a particular borrower type appear to provide a greater amount of future loan volume? Also, we contend that if H_2 is rejected, the survey respondents were able to formulate an opinion about a specific market segment or identify a specific market segment, which gives credence to the market segmentation or typology presented to the respondents. Since the data collected are ordinal, we follow Conover and Iman's (1981) tie-corrected Wilcoxon signed rank test (WSRT) to test H_2. This nonparametric test is analogous to a pairwise t-test. Finally, we test if there is a difference between senior officials' and loan officers' perceptions of expected loan volume growth via the Kruskal-Wallis nonparametric test.

Survey Results

Table 1 shows the average years of experience with Farm Credit for loan officers and senior officials plus their opinions relative to important factors—interest rates, Farm Credit's reputation, and lending relationship—in obtaining and attracting new loans. Years of experience for both loan officers and senior officials are similar, with respective averages of 13.3 and 14.29. Interest rates, reputation, and lending relationship are rated on a scale of importance, with 1 = very low and 10 = very high.

The results show that interest rates are clearly perceived to be the most important factor in obtaining new loans. One loan officer rated interest rates as being very low (2), while nearly all other respondents felt this factor was very important, ranking it at least 8 or greater. Consequently, no statistically significant difference is found between the opinions of loan officers and senior officials on the importance of interest rates and the lending relationship in obtaining new loans. A significant difference is noted, however, on Farm Credit's reputation, which means H_1 is rejected for this perception. In the survey, senior officials state that reputation is more important to them in obtaining and retaining loans, while loan officers indicate reputation is not as important.

Characteristics of the Borrower Types

Senior officials and loan officers ranked, on a scale from 1 to 10 (with 1 = very low and 10 = very high), the competitiveness of Farm Credit in obtaining new loans and characteristics of specific borrower types.

Table 2. Competitiveness in Obtaining New Loans and Characteristics of Different Borrowers Within the Oklahoma Farm Credit Associations

Description		Mean	Minimum	Median	Maximum	Kruskal-Wallis Test
How competitive is FCA in obtaining new loans from each borrower type?[a]						
Full-Time Farmer	Loan Officers	8.15	6.00	8.00	10.00	0.04
	Senior Officials	8.08	5.00	8.00	10.00	
Part-Time Farmer	Loan Officers	6.85	3.00	7.00	10.00	0.03
	Senior Officials	7.04	5.00	7.00	10.00	
Lifestyle Farmer/Landowner	Loan Officers	6.44	2.00	7.00	10.00	0.00
	Senior Officials	6.50	3.00	7.00	9.00	
How would you rate the repayment capacity of each borrower type?						
Full-Time Farmer	Loan Officers	6.19	3.00	7.00	8.00	8.60***
	Senior Officials	7.46	3.00	8.00	10.00	
Part-Time Farmer	Loan Officers	7.44	5.00	8.00	10.00	0.78
	Senior Officials	7.75	5.00	8.00	10.00	
Lifestyle Farmer/Landowner	Loan Officers	7.59	5.00	8.00	10.00	0.75
	Senior Officials	7.83	4.00	8.00	10.00	
How would you rate the solvency of each borrower type?						
Full-Time Farmer	Loan Officers	6.37	2.00	7.00	10.00	2.30
	Senior Officials	7.21	5.00	7.00	10.00	
Part-Time Farmer	Loan Officers	5.78	4.00	6.00	8.00	14.88***
	Senior Officials	7.54	5.00	8.00	10.00	
Lifestyle Farmer/Landowner	Loan Officers	6.19	2.00	7.00	9.00	10.99***
	Senior Officials	7.79	3.00	8.00	10.00	
How would you rate the loyalty of each borrower type?						
Full-Time Farmer	Loan Officers	7.41	2.00	8.00	10.00	0.25
	Senior Officials	7.79	5.00	8.00	10.00	
Part-Time Farmer	Loan Officers	5.67	2.00	6.00	9.00	3.99**
	Senior Officials	6.75	4.00	7.00	9.00	
Lifestyle Farmer/Landowner	Loan Officers	4.93	2.00	5.00	8.00	0.01
	Senior Officials	4.96	1.00	5.00	9.00	

Note: Double and triple asterisks (*) denote statistical significance at the 5% and 1% levels, respectively.
[a] $N = 51$ total respondents (27 loan officers and 24 senior officials), with answers on a scale from 1 to 10 (1 = very low; 10 = very high).

The results are presented in Table 2. Of interest is that no statistically significant difference exists between loan officers and senior officials about how competitive Farm Credit is in obtaining new loans from full-time, part-time, and lifestyle farmers. Thus, H_1 cannot be rejected for this perception since senior officials and loan officers both agree that Farm Credit is most competitive in obtaining new loans with full-time farmers. In the comments portion of the survey, a few respondents stated that full-time farmers are their primary customers, and because of this, they are most competitive in obtaining loans from full-time farmers. Both senior officials and loan officers are the least optimistic about how competitive Farm Credit is in obtaining new loans from the lifestyle farmer group. Possibly this mindset is a result of not having full access to this group because of restrictions in Farm Credit's legal authorization. This thinking may also indicate that lifestyle farmers are already established with another commercial bank and may not need additional credit from other sources.

The financial characteristics of each borrower type provide evidence of a divergence in the opinions of senior officials and loan officers. Senior officials' perceptions about the repayment capacity of full-time farmers are higher than the perceptions of loan officers. This result may be influenced by loan officers having direct contact with full-time farmers and hearing about the difficulties these farmers experience in meeting cash demands as they come due. Based on the Kruskal-Wallis test, H_1 is rejected—i.e., senior officials' and loan officers' perceptions of repayment capacity of full-time farmers are different. The solvency of a borrower provides protection against financial risks. Loan officers feel that part-time and lifestyle farmers have a much lower solvency position compared to the perceptions of their senior official counterparts. This difference of opinion could be because senior officials are more familiar with the wealth profile of this emerging market segment. H_1 is rejected for the perception concerning the solvency of part-time farmers and lifestyle farmer/ landowners.

The perceived loyalty of borrowers to Farm Credit is an important aspect of the lending relationship. Both loan officers and senior officials agree that full-time farmers are the most loyal borrower type, an encouraging finding since this is their primary customer. Part-time and lifestyle farmers were perceived to be the least loyal to Farm Credit. This could be explained by the fact that commercial banks are already meeting these borrowers' needs, or because Farm Credit does not have a long-term relationship with them. Loan officers' and senior officials' opinions regarding the loyalty of the different market segments only diverge in the case of part-time farmers; therefore, H_1 is rejected for this perception. Senior officials are more optimistic than loan officers about the loyalty of part-time farmers. Potentially, loan officers hold a more accurate view of customer loyalty because they have day-to-day contact with these borrowers. If this is the case, it is an important point for OFCA since Moss, Barry, and Ellinger (1997) found that lending relationships are important to increasing customer loyalty.

Expected Loan Growth of the Different Borrower Types

The survey also explored perceptions as to which market segment provides the highest loan growth potential for Farm Credit. Figure 1 is a histogram of all survey responses relative to the expected loan volume growth of each borrower type over the next three years. No respondents feel that the loan volume of lifestyle farmers would decrease, while only two respondents indicate there would be a reduction in loan volume for part-time farmers. Based on this result, part-time and lifestyle farmers provide the best opportunity for loan volume growth. However, the responses are more varied for full-time farmers. Half of the respondents feel that the loan volume of full-time farmers would be zero or less. Examining the histogram is informative, but it does not identify whether the potential loan volume growth is statistically different for each borrower type and whether senior officials' and loan officers' opinions are different. To test if there is a statistical difference between borrower types and opinions of senior officials and loan officers, the percentage of loan volume growth for each borrower type is calculated from the histogram.

Table 3 reports the results showing which borrower type the senior officials and loan officers feel will have the most loan volume growth over the next three years for Farm Credit. Collectively, the sample respondents feel that full-time farmers present the lowest average amount of expected loan volume growth (0.78%). Part-time farmers present the best opportunity to increase loan volume based on the entire sample (13.53%), and lifestyle farmers/landowners present an average expected loan volume growth of 11.27%.

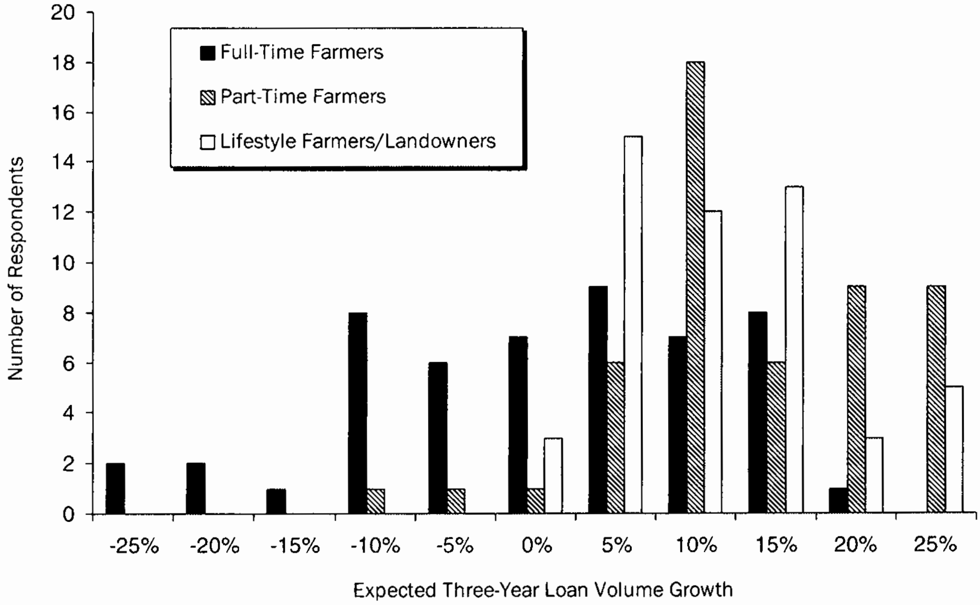

Figure 1. All Survey Responses to the Expected Three-Year Loan Volume Growth by Borrower Type

Table 3. Expected Three-Year Loan Volume Growth by Borrower Type

Borrower Type	All Observations Mean / (SD)	Loan Officers Mean / (SD)	Senior Officials Mean / (SD)	Kruskal-Wallis Test
Full-Time Farmer	0.78% ^{B,C}	−0.56%	2.29%	1.68
	(1.57%)	(1.50%)	(2.92%)	
Part-Time Farmer	13.53% ^{A,C}	15.93%	10.83%	2.67
	(1.11%)	(1.14%)	(3.91%)	
Lifestyle Farmer/Landowner	11.27% ^{A,B}	12.78%	9.58%	1.82
	(0.96%)	(0.86%)	(2.61%)	

Notes: Standard deviations (SD) are numerically bootstrapped using 1,000 iterations. The superscript letters A, B, and C represent the corrected Wilcoxon signed rank test, which is a pairwise comparison for all observations of full-time farmer, part-time farmer, and lifestyle farmer/landowner, respectively. Each test is statistically significant at the 1% level, and p-values were calculated via 10,000 Monte Carlo simulations.

The numerically estimated standard deviations indicate survey respondents are most certain that part-time and lifestyle farmers/landowners will show more loan volume growth compared to full-time farmers. Based on results of the WSRT, there is a significant statistical difference between the expected loan volume growth for each borrower type, which means H_2 is rejected in this case. This statement provides evidence that respondents in the survey sample were able to delineate among the different types of borrowers presented to them.

In contrast to the previous results on borrower types' characteristics and Farm Credit's reputation, the Kruskal-Wallis test does not indicate that the perceptions of senior officials and loan officers about future loan growth for the market segments are statistically different; therefore, H_1 cannot be rejected for this perception. This survey result reveals that all levels of OFCA agree part-time farmers and lifestyle farmers present the best opportunity for loan volume growth.

Implications and Conclusions

The results of our survey suggest some important differences in attitudes within the management teams and staff of Oklahoma Farm Credit Associations (OFCAs) toward nontraditional loan customers. Loan officers rated solvency of part-time farmers, solvency of lifestyle farmers/landowners, and loyalty of part-time farmers lower than did senior officials. These differences are important because individuals within an FCS association who formulate the market segmentation strategy (senior officials) and individuals who implement the strategy (loan officers) do not necessarily agree about the characteristics of these segments.

The results also indicate that management and staff within the levels of OFCA disagree on Farm Credit's reputation and competitiveness within each borrower segment. Senior officials, who set the strategic direction, are more positive about the characteristics of nontraditional loans for Farm Credit, and they have a more optimistic view of Farm Credit's competitiveness in these segments. These findings suggest the need for better communication between loan officers and senior officials. Dialog between the loan officers and senior officials could alleviate many of these discrepancies and could allow these organizations to develop a more cohesive marketing strategy.

Identifying these differences is possible because senior officials and loan officers within OFCA were able to delineate among the presented borrower types. Even though there are differences, a consensus does exist within OFCA that the part-time and lifestyle market segments present the best opportunity for loan volume growth. This consensus agrees with the findings of the Farm Credit HORIZONS project—the growth of "nontraditional" farmers, or farmers who spend a majority of their time working off the farm, has increased—and reemphasizes the need for Farm Credit to pursue market segmentation strategies or risk losing these markets to other lenders.

The results of our survey also show that OFCA employees feel part-time and lifestyle/landowner farmers provide the best opportunity for loan volume growth, yet they identify these borrowers as being the least loyal to the FCS. To enhance this group's loyalty, OFCA can use one of its strategic advantages over commercial banks, the patronage program. Since OFCA is a borrower-owned cooperative, it has the ability to share a portion of its earnings with OFCA member borrowers through the patronage program. Jorgensen (2007) found that current East Central Farm Credit of Oklahoma (ECFCO) customers prefer an increase in patronage payments over a reduction in fixed interest rates. In other words, the average customer for ECFCO greatly values the patronage program. Potentially, this high value placed on the patronage program is a way for OFCA to increase the loyalty of its nontraditional loan customers.

We have outlined some basic components of market segmentation by exploring the opinions of OFCA loan officers and senior officials. Even though OFCA is relatively small and may not be able to implement a complex market segmentation strategy similar to larger Farm Credit Associations, this study and discussion should be helpful in encouraging OFCA to move beyond HORIZONS.

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Credit Risk Rating Migration and Unobserved Borrower Heterogeneity

Jeffrey R. Stokes, Jonathan B. Dressler, and Lakshmi Balasubramanyan

Abstract

Some past studies of credit risk ratings migration have found trend reversals and evidence that the data-generating process is nonstationary. Using a sample of Farm Credit System mortgages, we find no compelling statistical evidence of either phenomenon. We do find evidence that our sample of loans may be characterized by two types of borrowers—namely, movers and stayers. This type of borrower heterogeneity is unobserved because movers who do not migrate are indistinguishable from stayers who never migrate. We report on the development of a flexible nonparametric model for estimating transition probabilities. The model can also be used to estimate nonstationary transition probabilities and an example is provided.

Key words: credit risk, Markov chain, maximum entropy, migration, risk ratings

Credit risk migration matrices are important inputs for many pricing and risk management applications. With respect to corporate bonds, the matrices are used to quantify the likelihood that a bond with a given rating will transition to another rating or stay the same over a specified period of time. For other fixed-income securities such as mortgages, the matrices quantify the likelihood that a borrower's risk rating improves, stays the same, or deteriorates over time. In either case, portfolio quality changes can be assessed by coupling the estimated matrices with a valuation model for the fixed income securities in question. Portfolio quality changes can be used to monitor business performance, manage exposure to credit risk, and in the case of mortgages, help a bank manage its capital position.

There are many important issues to consider within the context of estimating transition probabilities for risk migration matrices. The standard approach used by ratings agencies such as Moodys, Standard and Poor's, or Fitch Ratings is to assume that a bond's risk rating migrates according to a stationary, first-order Markov chain. Maximum-likelihood (ML) estimation of stationary transition probabilities for this type of stochastic process is straightforward since the ratings agencies have the requisite micro-level data showing the transition of each bond among risk rating categories over time.[1]

Building on work by Lee and Judge (1996), Stokes and Gloy (2007) show how to

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[1] See, for example, Anderson and Goodman (1957) for a maximum-likelihood estimator of stationary transition probabilities when micro-level data are available.

estimate stationary transition probabilities for loan delinquency and credit risk migration when micro-level data are unavailable. However, even when micro-level data are available, there are some potential problems with applying the standard approach in practice, especially for mortgages. First, a first-order Markov chain is merely an assumption and not a financial truth. In fact, Bahar and Nagpal (2001) find evidence of a "momentum" effect wherein bond ratings changes are more likely to be followed by similar ratings changes.

Research by Phillips and Katchova (2004) using credit score proxies, and Behrens and Pederson (2007) examining Farm Credit System (FCS) loans, suggests that trend reversals (i.e., downgrades followed by upgrades and upgrades followed by downgrades) are apparent. Although both studies attribute these trend reversals to nonstationarity, it may actually be evidence that the stochastic process generating risk ratings is a second- or higher-order Markov chain (which may or may not be stationary), or perhaps not Markov at all.

Even so, the stationarity assumption associated with the standard approach is thought to be particularly restrictive. Like their stationary counterparts, ML estimation of nonstationary transition probabilities and the testing of stationarity are also straightforward.[2] However, the resulting ML transition probabilities are merely time dependent. If risk rating migration is nonstationary, it is obviously more interesting and potentially more useful to condition the estimation of the transition probabilities on relevant economic information. As noted by Golan, Judge, and Miller (1996), without a sufficiently long time series, degrees-of-freedom issues can quickly render the estimation problem ill-posed and underdetermined.

[2] Again, Anderson and Goodman (1957) present a maximum-likelihood estimator for nonstationary transition probabilities as well as a test for stationarity for a first-order Markov chain.

Additionally, it is an empirical regularity that some firms' risk ratings never change while others change on a fairly regular basis. With the standard Markov chain approach, obligor risk ratings are assumed to be homogeneous with respect to their movement behavior among ratings categories. Hamilton and Cantor (2004) and Duffie, Wang, and Saita (2006) suggest risk ratings may not be Markov due to borrower heterogeneity. Behrens and Pederson (2007) also suggest a type of borrower heterogeneity in that seasoned FCS loans tend to migrate less than unseasoned loans. Interestingly, Frydman and Kadam (2004) report the exact opposite for corporate bonds.

Frydman, Kallberg, and Kao (1985); Frydman and Kadam (2004); and Frydman (2005) propose a mover-stayer (MS) model as an alternative model of risk rating migration when unobserved heterogeneity is present. In this model, the stayer's movement is characterized by an identity matrix (i.e., stayers never migrate), while movers migrate according to a first-order Markov chain. In this case, the heterogeneity is unobserved because not all the movers move each period, making it impossible to observe how many stayers are in the population.

It is important to note that the stochastic process generating risk rating migration consisting of two independent first-order Markov chains, one for movers and one for stayers, is a mixed process and is itself not a Markov chain (first order or otherwise). Therefore, the existence of unobserved borrower heterogeneity necessarily implies that the ML estimation of transition probabilities and any subsequent tests, whether from a stationary process or not, are inappropriate.

The objective of this study is to report on the development of a flexible nonparametric econometric model for estimating transition probabilities for risk rating migration matrices. The model is an entropy-based econometric model, and therefore accommodates limited data (i.e., a short time series and/or a large state space) by default. Additionally, the model can capture unobserved heterogeneity in an MS framework, yet nests homogeneity as a special case. The model can also be specified in a nonstationary setting allowing for the accommodation of economic information in the estimation of the model parameters.

In the following sections, we briefly discuss literature making use of the standard approach for estimating risk migration matrices. We then propose an alternative approach for estimating stationary and nonstationary risk migration matrices. Using a sample of FCS loans, we compare the impact of the different estimates on the value-at-risk of a portfolio of loans.

ML Estimation of Risk Ratings Migration Matrices

Risk rating migration is typically modeled as a first-order Markov chain where the states of the chain are borrower or loan risk ratings. Stationary transition probabilities, p_{ij}, represent the probability that borrowers with risk rating i migrate or transition to risk rating j over a specified period of time, such as a year. A matrix of these probabilities, **P**, can be estimated via the method of maximum likelihood if a time series of micro-level (i.e., account-level) data is available. Assuming a stationary, first-order Markov chain is appropriate, the ML estimator for the transition probabilities is given by:

$$(1)\quad \hat{p}_{ij} = \frac{n_{ij}}{\sum_j n_{ij}},$$

where n_{ij} is the observed number of borrowers who had risk rating i at time t and have risk rating j at time $t + 1$.

Barry, Escalante, and Ellinger (2002); Escalante et al. (2004); Phillips and Katchova (2004); and Deng et al. (2007) all use (1) to estimate the probability that the risk rating for Illinois Farm Business Farm Management Association members' businesses transition among five credit score classes. It is important to point out that lender data were not used in any of these studies. The producer data used are assumed to proxy actual loan performance that might be experienced by a bank having a financial relationship with these businesses.

Phillips and Katchova (2004) suggest the Markov assumption of independence is violated, while Deng et al. (2007) argue there is little evidence to reject the assumption. In both cases, however, the analyses conducted are for testing stationarity of a first-order Markov chain. Although stationarity is an issue worthy of investigation, testing the order of the Markov chain is perhaps a more critical first step, especially in light of trend reversals or momentum. If there are trend reversals or momentum in ratings migration, knowing that i is the current rating is insufficient for determining the probability of transitioning to risk rating j, since one would need to know something about one or more of the previous period's risk ratings. For example, upgrades being more likely to be followed by downgrades (i.e., trend reversal) could be consistent with a stationary (or nonstationary) second-order Markov chain with transition probability p_{kij} [$p_{kij}(t)$ in the nonstationary case].

Gloy, LaDue, and Gunderson (2005) and Behrens and Pederson (2007) apply (1) to estimate first-order stationary transition probabilities for borrower risk ratings using actual bank data. In the former case, data were pooled from commercial and FCS sources and a common five-tier risk rating system was employed to estimate the transition probabilities. In the latter case, FCS borrowers from AgriBank were risk rated according to a nine-point scale and the transition probabilities estimated from these data.

One improvement in these research efforts when compared to the previously cited research is the use of data from the lender's actual clientele. When compared to the research making use of credit score proxies, retention rates (i.e., the probability of remaining in the same risk rating category) tend to be higher. This implies that transition probabilities estimated from actual lender data are suggestive of less probability of upgrades or downgrades from a given risk rating.

Even so, Behrens and Pederson (2007) find evidence of trend reversal, or what they refer to as path dependence, and use a test statistic developed by Anderson and Goodman (1957) for determining whether estimated transition probabilities for a first-order Markov process are stationary or nonstationary. As noted above, trend reversal could be consistent with a second- (or higher-) order Markov chain that may or may not be stationary. A test of the null hypothesis of a first-order Markov chain against the alternative of a Markov chain of order r is also given by Anderson and Goodman. Testing for stationarity after testing the order of the process appears to be a more logical progression.

Also calling into question the use of (1) above is the generally held belief that the stochastic process generating risk ratings is stationary. While maximum likelihood can also be used to estimate nonstationary transition probabilities arising from Markov chains, say $p_{ij}(t)$ in the first-order case, the resulting probabilities are not linked to the economic information that presumably influences them over time. It is possible to directly link the estimation with relevant economic information such as $p_{ij}(t) = f(\mathbf{X}\boldsymbol{\beta})$. However, degrees-of-freedom issues quickly become a problem for even a modestly sized matrix of explanatory variables $\mathbf{X}$ since the parameter vector $\boldsymbol{\beta}$ can meet or exceed the number of sample data points required for estimation. In addition, there is no guidance on the functional form of the relationship between the covariates and the probabilities.

Compounding the issue of estimation in light of a nonstationary Markov chain is the research cited above that the Markov model, in its strictest form, may not be applicable for risk ratings. Unobserved heterogeneity means some borrowers never get upgraded or downgraded, while others experience upgrades and/or downgrades on a frequent basis. It is likely the case that the strength (or lack of strength) of a borrower's financial position may be the primary reason a borrower's risk rating does not change.

Conceptually, one of the simplest models to account for this type of heterogeneity is the mover-stayer (MS) model originally proposed by Blumen, Kogan, and McCarthy (1955). In the MS model, the transition probability matrix, $\mathbf{P}$, is a mixture of two independent first-order Markov chains but is itself not a Markov chain. The movers transition according to the Markov matrix $\mathbf{M}$, while the stayers' transitions are characterized by an identity matrix and a vector $\mathbf{S}$ showing the proportion of stayers in a given state. In matrix terms, $\mathbf{P}$ is decomposed in the following manner:

(2) $\mathbf{P} = \mathbf{SI} + (\mathbf{I} - \mathbf{S})\mathbf{M}$,

where $\mathbf{I}$ is a $Q \times Q$ identity matrix with Q states (risk rating classes).

The difficulty in estimating transition probabilities in the MS model arises for at least two reasons. First, while stayers do not move with probability one, movers may move or stay over a transition, which makes distinguishing between stayers and movers who stay very difficult. It can also be difficult to generate consistent estimates of $\mathbf{P}$ for reasons related to the available time series.

Goodman (1961) improved upon Blumen, Kogan, and McCarthy's (1955) estimators for the transition probabilities characterizing the movers and proportion of stayers, where the latter's is dependent on the number of transitions (T) being sufficiently large so that $\mathbf{M}^T = \mathbf{M}^\infty$. Goodman also presents ML estimates for $\mathbf{M}$ and $\mathbf{S}$ when T is small so long as the number of observed units in each state is large. Frydman (2005) provides ML estimators for a continuous-time MS model specifically developed for bond ratings migration. Unfortunately, FCS's recent adoption of a 14-tier risk rating system implies none of Goodman's or Frydman's results are directly applicable, since the available time series is short.[3]

Entropy Estimation of Risk Rating Migration Matrices

Because risk rating migration may be non-Markovian due to borrower heterogeneity, and the number of transitions under the FCS's new 14-tier risk rating system is small, we suggest an alternative to the ML estimation of **P**. More specifically, we make use of an estimation technique uniquely designed to accommodate situations when T is small, or more appropriately, when $TQ < Q^2$ where Q represents the number of states or risk rating classes in **P**. The risk rating migration problem is ill-posed and underdetermined in this setting and represents an ideal situation for the use of entropy to select from among the infinite number of probability distributions characterizing the data-generating process.

It is important to point out that with more conventional (e.g., parametric) methods, estimating the parameters of the mover-stayer model are not possible given the data at hand. However, an entropy approach that accommodates the possibility of movers and stayers is not problematic if movers and stayers are not present in the population, as the estimated proportion of stayers can be zero (i.e., all movers). In this sense, the MS model nests a more restrictive entropy-based specification for estimating transition probabilities when borrower heterogeneity is not present or is ignored.

Following Golan, Judge, and Miller (1996), a simple maximum entropy formalism for the stationary first-order Markov problem is written as:

(3) $\max H(\mathbf{M}) = -\mathbf{M}'\ln(\mathbf{M}),$

subject to the moment consistency conditions

(4) $(\mathbf{I}_Q \otimes \mathbf{x}_{T-1})\mathbf{M} = \mathbf{x}_T,$

K additivity conditions

(5) $(\mathbf{1}' \otimes \mathbf{I}_Q)\mathbf{M} = \mathbf{1},$

and nonnegativity condition

(6) $\mathbf{M} \geq \mathbf{0}.$

In this system, $\mathbf{M}$ is a $Q^2 \times 1$ vector of transition probabilities, $\mathbf{1}$ is a $Q \times 1$ vector of ones, $\mathbf{x}_T$ is a $TQ \times 1$ vector of state outcomes for T transitions, and $\mathbf{x}_{T-1}$ is a $TQ \times Q^2$ matrix of state outcomes for T transitions. With $TQ < Q^2$, the matrix $(\mathbf{I}_Q \otimes \mathbf{x}_{T-1})$ is non-invertible.

The Shannon entropy function, $H(\mathbf{M})$, takes a maximum when the distribution of transition probabilities is uniform. The constraints of the system are given by the moment consistency equations in (4) which are collectively the first-order Markov assumption, additivity equations in (5) that ensure the states modeled are inclusive of the system under study, and the nonnegativity condition in (6) which ensures the estimated probabilities are proper probabilities.

The system (3)–(6) is an oversimplification in that it is a pure inverse problem and is therefore only appropriate when the data-generating process is first-order Markov and the data are observed without error. While entropy is an effective way to deal with the issue of so few data points, conventional tests of significance are not possible. Therefore, point estimates are likely less appealing than a distribution of probabilities from which estimation precision can be determined. Techniques have been developed by Soofi (1992, 1994) and Golan (1994) to measure estimate

[3] FCS implemented the 14-tier risk rating system in 2004 following Office of the Comptroller of the Currency (OCC) guidelines, where tier 1 represents minimal credit risk and tier 14 represents loss. Agricultural real estate loans do not qualify for tiers 1–3. Tiers 4–9 are termed "acceptable," while tier 10 is termed "special mention." Tiers 11 and 12 are both termed "substandard," the former being "viable" and the latter being "nonviable." Tier 13 is termed "doubtful." All borrowers/loans have been risk rated using the system since that time by AgChoice Agricultural Credit Association (our data source), implying only three years or two transitions of data under the new system.

precision and the importance of the contribution of information in reducing information uncertainty concerning the unknown probabilities.

The simple maximum entropy model presented above can be reparameterized to accommodate these limitations in a straightforward way. First, we augment the objective function and specify the entropy over all the unknown probabilities associated with the parameters to be estimated for the risk rating migration problem as well as the error that will apply to the moment consistency conditions in (4). The objective function to be maximized is now:

$$(7)\quad H(\mathbf{M}, \mathbf{S}, \mathbf{W}) = -\mathbf{M}'\ln(\mathbf{M}) - \mathbf{S}'\ln(\mathbf{S}) - \mathbf{W}'\ln(\mathbf{W}),$$

where $\mathbf{M}$ is the transition probability matrix for the movers, $\mathbf{S}$ is a matrix of the probabilities associated with the proportion of stayers, and $\mathbf{W}$ is a matrix of error probabilities. Let $\mathbf{u} = [u_1, u_2, \ldots, u_L]$ and $\mathbf{q} = [q_1, q_2, \ldots, q_L]$ be parameter support vectors and $\mathbf{v} = [v_1, v_2, \ldots, v_L]$ be an error support vector so that calculating $\hat{\mathbf{M}} = \mathbf{uM}$ is a matrix of expected (i.e., probability-weighted) mover transition probabilities. Similarly, $\hat{\mathbf{S}} = \mathbf{qs}$ is a vector of expected (i.e., probability-weighted) proportions of stayers, while $\hat{\mathbf{W}} = \mathbf{vW}$ is a matrix of errors associated with the moment consistency constraints to be specified below. While the parameter and error supports are all notated as having L elements, this need not be the case.

The moment consistency conditions reconcile mover transitions between risk rating categories each time period. Making use of the support vectors described above, this implies that the first-order Markov relation for the movers is:[4]

$$(8)\quad \mathbf{x}_T = (\mathbf{I}_Q \otimes \mathbf{x}_{T-1})\mathbf{uM} + \mathbf{vW}.$$

Similarly, the new additivity conditions imply:

$$(9)\quad \begin{aligned} (\mathbf{1}' \otimes \mathbf{I}_Q)\mathbf{uM} &= \mathbf{1}, \\ (\mathbf{1}' \otimes \mathbf{I}_Q)\mathbf{S} &= \mathbf{1}, \\ (\mathbf{1}_K' \otimes \mathbf{I}_Q)\mathbf{M} &= \mathbf{1}_Q, \\ (\mathbf{1}_K' \otimes \mathbf{I}_Q)\mathbf{W} &= \mathbf{1}_T, \end{aligned}$$

where these equations ensure that all the estimated probabilities in each row sum to one. Last, nonnegativity constraints for all probabilities are required whereby

$$(10)\quad \mathbf{M} \geq \mathbf{0},\ \mathbf{S} \geq \mathbf{0}, \text{ and } \mathbf{W} \geq \mathbf{0}.$$

The maximization of (7) subject to (8)–(10) results in estimates of discrete probability distributions of each mover transition probability, proportions of stayers, and errors. Using the parameter supports, $\mathbf{P}$ can be calculated via (2), or using the present notation:

$$(11)\quad \mathbf{P} = \mathbf{qSI}_Q + (\mathbf{I}_Q - \mathbf{qS})\mathbf{uM}.$$

Also, it is important to note that because entropy is additive (Behara, 1990), the model captures all of the parameter and error probability uncertainty in the objective function. Finally, if there is no unobserved heterogeneity in a risk rating category, there should be some empirical evidence that the proportion of stayers in a given risk rating category is zero. In this case, the model presented in (7) subject to (8)–(10) collapses to that of a stationary, first-order Markov chain with borrower homogeneity.

By default, the model presented above is consistent with a uniform prior for all parameter and error probabilities with information (i.e., data) suggesting whether departures from the uniform assumption are warranted. Non-sample information may be useful to incorporate, and the

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[4] The matrix representation of equation (8) masks some of the difficulty in estimating the transition probabilities in that not all of the movers move each period. In scalar form, equation (8) can be expressed as

$$x_j(t) = x_{jj}(t-1)m_{jj} + \sum_{i\neq j} x_{ij}(t-1)m_{ij} - \sum_{i\neq j} x_{ji}(t-1)m_{ji} + \sum_k v_k w_{jk}(t),$$

which more clearly shows that some of the $x_{jj}(t-1)$ are potentially stayers who never move, but the balance of the $x_{jj}(t-1)$ are movers who can, but may not be observed to move over the period.

model presented in this section can be expanded to allow for a non-uniform prior distribution.

For example, Gloy, LaDue, and Gunderson (2005) find that risk ratings do not typically move much from period to period, but when they do, there is more probability of a downgrade than an upgrade. An identity matrix prior, or something close to it, is therefore likely more useful non-sample information than the default prior.

More generally, allowing for any prior distributions for the mover, stayer, and error probabilities only influences the objective function (7). Let $\tilde{\mathbf{M}}$, $\tilde{\mathbf{S}}$, and $\tilde{\mathbf{W}}$ be matrices of prior probabilities so that minimizing

$$(12)\quad I(\mathbf{M}, \mathbf{S}, \mathbf{W}; \tilde{\mathbf{M}}, \tilde{\mathbf{S}}, \tilde{\mathbf{W}}) = \mathbf{M}'\ln\left(\frac{\mathbf{M}}{\tilde{\mathbf{M}}}\right) + \mathbf{S}'\ln\left(\frac{\mathbf{S}}{\tilde{\mathbf{S}}}\right) + \mathbf{W}'\ln\left(\frac{\mathbf{W}}{\tilde{\mathbf{W}}}\right)$$

subject to (8)–(10) is a generalized cross-entropy mover-stayer model.

Nonstationary estimation can also be accommodated in the present approach. As noted above, nonstationary transition probabilities arise when the probabilities of a transition are impacted in some way by economic information. For example, the price of a firm's output affects the ability of the firm to service debt. As output price falls, the probability of delinquency may rise, implying the probability of a downgrade in risk rating is imminent.

A variable such as output price could be included as a part of the estimation, although it is unclear how $\mathbf{M}$ should functionally depend on the variable. In keeping with Courchane, Golan, and Nickerson (2000) and Glennon and Golan (2003), we augment the moment consistency conditions in (8) in the following way. Let $\mathbf{z}_T$ be a $T \times F$ matrix of observations on a total of F factors or covariates measured for T transitions and assumed to affect the transition probabilities in some manner. Multiplying (8) through by $\mathbf{z}_T$ gives:

$$(13)\quad \mathbf{z}_T'\mathbf{x}_T = (\mathbf{I}_Q \otimes \mathbf{z}_T'\mathbf{x}_{T-1})\mathbf{uM} + \mathbf{z}_T'\mathbf{vW},$$

which can be used in place of (8) to estimate the nonstationary transition probabilities [i.e., minimizing (12) subject to (9), (10), and (13)]. We refer to this model as a generalized instrumental variable cross-entropy mover-stayer model. The importance of adding information can be gauged by calculating normalized entropy which measures the reduction in information uncertainty attributable to a covariate (Golan, Judge, and Miller, 1996).

Data, Empirical Estimation, and Tests

Shown in Table 1 are some summary statistics for data collected from AgChoice, one of the FCS's Agricultural Credit Associations operating in the majority of Pennsylvania counties and four counties in West Virginia. All loans in the sample were originated between 2004 and 2006, and all are fixed-rate loans made to dairy producers collateralized by farm real estate. Farm real estate loans to dairy producers represent the largest dollar asset in AgChoice' s portfolio. In all, 670 of these loans totaling about \$161 million were on the books at year-end 2005, while 658 loans totaling \$163 million were on the books at year-end 2006. Average risk ratings improved slightly from 2004 to 2005, and then appear more stable from 2005 to 2006.

With no loans in the first three risk rating categories, $Q = 10$ including a default state. Since our data correspond to the implementation of the 14-tier risk rating system adopted by AgChoice in 2004, $T = 3$ and there are two observed transitions for risk ratings. As noted, the short length of the time series is a key reason for using an entropy model to estimate transition probabilities, as is any possible heterogeneity that necessitates a mover-stayer framework. Short of this approach, it is likely that the standard approach [i.e., equation (1)] is the only way to estimate transition probabilities.

Table 1. Summary Statistics for FCS Sample of Fixed-Rate Loans to Dairy Producers

Statistic	Loan Amount ($)	Interest Rate (%)	Risk Rating 2004	Risk Rating 2005	Risk Rating 2006
Mean	239,856	6.84	7.3	6.6	6.6
Median	169,976	6.85	7.0	7.0	7.0
Mode	100,000	6.25	9.0	4.0	4.0
Standard Deviation	255,232	0.79	2.0	2.3	2.3
Minimum	6,859	3.00	4.0	4.0	4.0
Maximum	2,200,000	9.15	12.0	12.0	12.0

For comparison purposes between the stationary and nonstationary MS model results to follow, Table 2 reports the results of applying (1) to the data under the assumption that risk ratings are generated by a stationary first-order Markov chain with borrower homogeneity. Visually, the empirical probabilities do not appear to be stationary. In addition, some of the retention probabilities are similar in magnitude to those reported by Gloy, LaDue, and Gunderson (2005) and Behrens and Pederson (2007). This is especially true for the second matrix, and in general for more highly rated borrowers. Moreover, there tends to be greater probability of loans upgrading than downgrading for nearly every risk rating class.

A test statistic was developed by Anderson and Goodman (1957) for testing the null hypothesis that risk ratings are a stationary first-order Markov chain against the alternative hypothesis that risk ratings are a stationary second-order Markov chain.[5] The statistic is expressed as:

$$(14)\quad \chi^2 = \sum_i \left[\sum_k \sum_j n^{*}_{ki} \left(\hat{p}_{kij} - \hat{p}_{ij} \right)^2 \Big/ \hat{p}_{ij} \right],$$

where

$$n^{*}_{ki} = \sum_j n_{kij},\ \hat{p}_{ij} = \sum_k n_{kij} \Big/ \sum_k \sum_l n_{kil}$$

are ML estimates for a first-order Markov chain, and

$$\hat{p}_{kij} = n_{kij} \Big/ \sum_l n_{kil}$$

are ML estimates for a second-order Markov chain. We estimate $\chi^2 = 167.1$ using our data so that with $Q(Q-1)^2 = 810$ degrees of freedom, we fail to reject the null hypothesis and conclude that if the data-generating process is stationary and Markov, there is no statistical evidence it is a second-order process.[6] Therefore, we conclude there is no statistical evidence in support of trend reversals or momentum in risk ratings migration in this portion of AgChoice's loan portfolio. This test statistic should be used for other research, most notably Behrens and Pederson (2007), as their data are derived from an FCS source as well.

Having established there is no empirical support for a second-order process, it remains to be determined whether there is empirical evidence that the first-order transition probabilities are stationary. Again, Anderson and Goodman (1957) develop a test statistic for testing the null hypothesis that risk ratings are a stationary first-order Markov chain against the alternative hypothesis that risk ratings are a nonstationary first-order Markov chain:

[5] Anderson and Goodman (1957) present a statistic for testing the null of a first-order chain against the alternative of an rth-order chain. For our data, $T = 3$ and a second-order chain is the only possibility. Even so, the trend reversal noted by other researchers makes the second-order chain potentially more important to test for anyway.

[6] A test statistic for first versus second order by risk rating category, χ^2_i is given by the bracketed term in (14) with $(Q-1)^2 = 81$ d.f. No individual risk ratings exhibit second-order tendencies in favor of first order at any reasonable level of significance.

Table 2. Maximum-Likelihood Estimates of Stationary Transition Probabilities for 2004–2005 and 2005–2006 FCS Risk Rating

		2005 Risk Rating									
		4	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**D**
2004 Risk Rating	**4**	97.02%	2.54%	0.00%	0.44%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
	5	27.65%	58.28%	10.58%	0.00%	3.49%	0.00%	0.00%	0.00%	0.00%	0.00%
	6	36.89%	1.05%	54.17%	4.73%	0.00%	3.17%	0.00%	0.00%	0.00%	0.00%
	7	38.60%	0.70%	1.01%	51.67%	0.00%	8.02%	0.00%	0.00%	0.00%	0.00%
	8	22.43%	0.00%	2.19%	2.86%	59.59%	12.93%	0.00%	0.00%	0.00%	0.00%
	9	9.97%	0.00%	0.00%	2.34%	1.06%	82.92%	2.98%	0.00%	0.00%	0.72%
	10	2.00%	0.00%	0.00%	0.00%	3.02%	40.78%	50.26%	2.15%	1.78%	0.00%
	11	0.00%	0.00%	0.00%	0.00%	0.00%	66.37%	20.64%	10.51%	2.48%	0.00%
	12	6.50%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	59.27%	34.24%
	D	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	100.00%

		2006 Risk Rating									
		4	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**D**
2005 Risk Rating	**4**	95.59%	0.00%	0.23%	2.57%	0.00%	0.30%	0.00%	1.14%	0.00%	0.17%
	5	24.42%	69.35%	6.23%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
	6	0.00%	3.49%	91.47%	0.00%	0.00%	5.04%	0.00%	0.00%	0.00%	0.00%
	7	1.39%	0.52%	4.66%	78.87%	4.80%	9.76%	0.00%	0.00%	0.00%	0.00%
	8	0.00%	0.00%	0.00%	4.76%	79.89%	8.04%	0.00%	0.00%	0.00%	7.32%
	9	0.00%	0.00%	0.00%	8.45%	11.17%	58.25%	10.75%	7.98%	0.00%	3.40%
	10	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	53.60%	34.50%	11.90%	0.00%
	11	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	100.00%	0.00%	0.00%
	12	0.00%	0.00%	0.00%	0.00%	0.00%	9.83%	0.00%	0.00%	90.17%	0.00%
	D	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	100.00%

(15) $\chi^2 =$

$$\sum_t \left[\sum_i \sum_j n_i(t-1) \left[\hat{p}_{ij}(t-1) - \hat{p}_{ij} \right]^2 / \hat{p}_{ij} \right],$$

which has the usual limiting distribution with $Q(Q-1)(T-1) = 180$ degrees of freedom. We estimate $\chi^2 = 176.8$, and thus fail to reject the null that risk ratings are a stationary process.[7]

This result is not entirely surprising given the short time span of the data (three years) and is actually consistent with previous research for bonds. For example, Kiefer and Larson (2004) find evidence of a stationary process for bond ratings migration for periods up to four or five years. They recommend reestimating the transition probabilities after this amount of time has passed. Behrens and Pederson (2007) reject stationarity using a sample spanning about 6½ years.

As noted above, if there is heterogeneity in the population of borrowers, there is no way to estimate the proportion of stayers in a sample of mortgages using the parametric results from Blumen, Kogan, and McCarthy (1955); Goodman (1961); or Frydman (2005). As an alternative, consider that an upper bound on the number of stayers is given by the diagonal of $\hat{\mathbf{P}}$, where $\hat{\mathbf{P}}$ is any estimate of $\mathbf{P}$ (e.g., maximum-likelihood estimate). This implies $\hat{\mathbf{S}} = \text{diag}\{\mathbf{P}\}$ is potentially useful information. The diagonals of the matrices of stationary transition probabilities estimated using all three time periods (not presented) are potentially a mixture of movers and stayers, and therefore represent the maximum number of potential stayers.

To conduct the entropy estimation, we let $L = 5$, and the parameter supports were specified as $\mathbf{u} = \mathbf{q} = [0\ \tfrac{1}{4}\ \tfrac{1}{2}\ \tfrac{3}{4}\ 1]$; the error support vector was specified as $\mathbf{v} = [-100\ -50\ 0\ 50\ 100]$. In the former case, the mover transition probabilities and proportion of stayers are all nonnegative and bounded by zero and one, making the choice of parameter supports straightforward. Through the choice of the error support, the errors are symmetric about zero and are of a magnitude consistent with the data on the number of borrowers used in equation (8).

Minimizing (12) subject to (8)–(10) using $\tilde{\mathbf{S}} = \text{diag}\{\hat{\mathbf{P}}\}$, $\tilde{\mathbf{M}} = \hat{\mathbf{P}}$, and prior error probabilities that are uniform, results in the transition probability matrix presented in Table 3.[8] This risk rating migration matrix is a first-order Markov chain for the movers in the sample. The system-normalized entropy for these results is 0.2013, which indicates a reasonably high level of overall estimate precision since the value is relatively far from one. The most notable difference between this matrix and typical risk rating transition probability matrices is the lack of probability mass on the main diagonal implying virtually zero rating retention rates for the movers. Risk rating class 9 is a notable state where there is a 5.62% probability of retention for a mover with this risk rating.

Presented in Table 4 are the estimated distributions of the proportions of stayers in each risk rating category along with the expected value and normalized entropy measures. The system-normalized entropy for these results is 0.3759, which also indicates a reasonably good level of overall estimate precision. With the exception of risk rating category 11, the estimated proportions of stayers in the sample are all relatively high. Additionally, in most cases, the normalized entropy for each risk rating category, which measures the precision of the stayer estimates, is reasonably low. While there is little empirical support for stayers in risk rating categories 10 and 11, there is strong support for stayers in risk rating category 9.

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[7] A test statistic for stationarity by risk rating category, χ_i^2 is given by the bracketed term in (15) with $(Q-1)(T-1) = 18$ d.f. Risk ratings 7, 9, and 11 do appear to exhibit nonstationary tendencies at the 5% level of significance.

[8] Space limitations preclude the presentation of all the estimated $\hat{m}_{ijl}$ (i.e., the elements of $\mathbf{M}$). We therefore present only the $\hat{m}_{ij} = \Sigma_l\, m_{ijl}$.

Table 3. Minimum Cross-Entropy Estimates of Stationary Mover Transition Probabilities for FCS Risk Rating Classes

	4	5	6	7	8	9	10	11	12	D
4	0.00%	21.77%	3.95%	46.91%	0.00%	5.17%	0.00%	19.35%	0.00%	2.86%
5	72.00%	0.00%	22.77%	0.00%	5.23%	0.00%	0.00%	0.00%	0.00%	0.00%
6	70.57%	6.91%	0.00%	8.56%	0.00%	13.95%	0.00%	0.00%	0.00%	0.00%
7	59.01%	1.40%	5.31%	0.00%	4.07%	30.21%	0.00%	0.00%	0.00%	0.00%
8	35.99%	0.00%	3.31%	9.09%	0.00%	44.43%	0.00%	0.00%	0.00%	7.19%
9	8.65%	0.00%	0.00%	18.16%	22.46%	5.62%	20.09%	16.60%	0.00%	8.40%
10	1.61%	0.00%	0.00%	0.00%	2.43%	57.80%	0.00%	27.75%	10.41%	0.00%
11	0.00%	0.00%	0.00%	0.00%	0.00%	89.95%	8.98%	0.00%	1.07%	0.00%
12	10.27%	0.00%	0.00%	0.00%	0.00%	35.70%	0.00%	0.00%	0.00%	54.03%

Table 4. Minimum Cross-Entropy Estimates of the Distribution of Stayers by Risk Rating Category

	Parameter Support Value						
Risk Rating	**0.00**	**0.25**	**0.50**	**0.75**	**1.00**	$\hat{s}_i$	**Normalized Entropy**
4	0.03%	0.22%	1.60%	11.76%	86.40%	96.07%	0.2858
5	1.31%	3.44%	9.04%	23.76%	62.46%	85.65%	0.6371
6	0.36%	1.37%	5.16%	19.49%	73.63%	91.16%	0.4822
7	1.11%	3.07%	8.45%	23.27%	64.10%	86.54%	0.6152
8	0.46%	1.62%	5.73%	20.31%	71.88%	90.38%	0.5073
9	0.00%	0.00%	0.07%	2.55%	97.38%	99.33%	0.0773
10	3.77%	7.18%	13.66%	25.98%	49.42%	77.52%	0.7973
11	33.88%	24.83%	18.19%	13.33%	9.77%	35.07%	0.9435
12	0.02%	0.19%	1.45%	11.22%	87.12%	96.31%	0.2737
D	0.00%	0.00%	0.00%	0.00%	100.00%	100.00%	0.0000

This result is consistent with the estimated probability of retention for movers with a risk rating of 9 presented above. Further, there is reasonably strong support for stayers in the remaining risk rating categories, especially 4 and 12.

Taken together, these results are reasonable in that risk ratings 4 and 12 are the highest and lowest risk ratings. Loans with the highest (lowest) risk rating probably go to farms with the strongest (weakest) financial position. Because it takes awhile for a financial position to deteriorate (improve), it is likely the case that stayers exist in these classes owing to inertia in their financial position. Risk rating 9 is somewhat similar although, at least in 2005, there were more loans with a risk rating of 9 than any other risk rating class (see Table 1).

An obvious question to ask in light of these results is why is there such a high proportion of stayers in risk rating class 9? An answer may be that fixed-rate dairy loans in AgChoice's portfolio do not get their ratings adjusted very often. On a more substantive level, however, this is probably a good question for AgChoice to address—since this FCS association either sees no reason to upgrade or downgrade loans carrying a risk rating of 9, or just isn't doing it.

Table 5 gives the estimated risk rating migration matrix (i.e., the matrix[9] of $\hat{p}_{ij}$) consisting of a mixture of the two Markov matrices for movers and stayers. This matrix is constructed by applying equation (2) using the estimates from Tables 3 and 4. The most important differences between these estimates and those arising from ML estimation for a first-order Markov chain are the retention and default probabilities. Consistent with Frydman (2005), the probability of default by risk rating category in the presence of stayers is never higher than when there are no stayers.

Retention rates are also much higher in the MS framework. Below, we compare these results with other estimates of the risk rating migration matrix with respect to their impact on value-at-risk.

Although no compelling evidence was found to suggest risk rating migration is nonstationary over the short time span of our data, the estimation of nonstationary transition probabilities is still of interest for cases when the null hypothesis can be rejected. By way of an example, milk prices and annual volatility in milk prices are covariates that may influence risk rating migration. As milk prices decline, dairy producers may have trouble servicing debt, and this could easily result in delinquency or default. In either case, it is reasonable to assume that the borrower's numerical risk rating is positively related to the price of milk. Similarly, contemporary financial theory would indicate that as the volatility of the firm's output price changes, the firm faces a changing level of business risk. How the firm responds to changes in business risk may also influence its risk rating, so borrower risk rating is also negatively related to volatility.

Table 6 presents a nonstationary transition probability matrix found by minimizing (12) subject to (9), (10), and (13) using lagged Pennsylvania state average wholesale milk price and the lagged annual volatility of Pennsylvania wholesale milk price as covariates that condition the estimation of the transition probability estimates (Pennsylvania Agricultural Statistics Service, 2006). Given no empirical evidence supporting nonstationarity, it is not surprising that the estimated matrix in Table 6 is nearly identical to the one presented in Table 5. The system-normalized entropy for the proportion of stayers is 0.3759, which is identical to that reported previously. With regard to the mover risk rating migration matrix, the system-normalized entropy is 0.2002, which represents a minuscule improvement in precision with the inclusion of the covariates. The reason the improvement is so small is attributable to

[9]This means that as milk prices fall (rise) the numeric risk rating value falls (rises), indicating a lower (higher) credit risk rating.

Table 5. Minimum Cross-Entropy Estimates of Stationary Transition Probabilities for FCS Risk Rating Classes

	4	5	6	7	8	9	10	11	12	D
4	96.07%	0.86%	0.16%	1.84%	0.00%	0.20%	0.00%	0.76%	0.00%	0.11%
5	10.33%	85.65%	3.27%	0.00%	0.75%	0.00%	0.00%	0.00%	0.00%	0.00%
6	6.24%	0.61%	91.16%	0.76%	0.00%	1.23%	0.00%	0.00%	0.00%	0.00%
7	7.94%	0.19%	0.71%	86.54%	0.55%	4.07%	0.00%	0.00%	0.00%	0.00%
8	3.46%	0.00%	0.32%	0.87%	90.38%	4.27%	0.00%	0.00%	0.00%	0.69%
9	0.06%	0.00%	0.00%	0.12%	0.15%	99.37%	0.14%	0.11%	0.00%	0.06%
10	0.36%	0.00%	0.00%	0.00%	0.55%	12.99%	77.52%	6.24%	2.34%	0.00%
11	0.00%	0.00%	0.00%	0.00%	0.00%	58.41%	5.83%	35.07%	0.70%	0.00%
12	0.38%	0.00%	0.00%	0.00%	0.00%	1.32%	0.00%	0.00%	96.31%	1.99%
D	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	100.00%

Table 6. Minimum Cross-Entropy Estimates of Nonstationary Transition Probabilities for FCS Risk Rating Classes

	4	5	6	7	8	9	10	11	12	D
4	96.07%	0.84%	0.16%	1.85%	0.00%	0.20%	0.00%	0.76%	0.00%	0.11%
5	10.38%	85.66%	3.22%	0.00%	0.74%	0.00%	0.00%	0.00%	0.00%	0.00%
6	6.34%	0.58%	91.16%	0.72%	0.00%	1.20%	0.00%	0.00%	0.00%	0.00%
7	8.25%	0.17%	0.63%	86.54%	0.49%	3.92%	0.00%	0.00%	0.00%	0.00%
8	3.54%	0.00%	0.30%	0.84%	90.38%	4.28%	0.00%	0.00%	0.00%	0.66%
9	0.06%	0.00%	0.00%	0.09%	0.10%	99.55%	0.09%	0.08%	0.00%	0.05%
10	0.36%	0.00%	0.00%	0.00%	0.55%	12.97%	77.51%	6.26%	2.35%	0.00%
11	0.00%	0.00%	0.00%	0.00%	0.00%	58.38%	5.85%	35.07%	0.70%	0.00%
12	0.38%	0.00%	0.00%	0.00%	0.00%	1.33%	0.00%	0.00%	96.31%	1.99%
D	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	100.00%

the fact that the transition probabilities offer no evidence of being nonstationary; thus, adding covariates to the estimation offers little improvement in estimate precision.

Comparison of Matrices and Methods

To compare the impact of the alternative methods of estimating risk rating migration matrices, we computed the 5% value-at-risk (VaR) for a portfolio of mortgages using the ML estimates for a stationary first-order Markov chain, and the entropy MS estimates for stationary and nonstationary stochastic processes. To compute the value-at-risk, we assume a portfolio of fixed-rate mortgages carrying a 6.5% interest rate and maturity of 20 years. Further, loss given default is assumed to be 10% in all cases.

Credit spreads for pricing the mortgages one period ahead were estimated for each risk rating category i by assuming the time zero value of the mortgages, $V_i(0)$, is the present value of the mortgages' value at time t, $V_i(t)$, discounted at the risk-free rate r plus the credit spread π_i. In continuous time, this implies $V_i(0) = V_i(t) \times \exp[(-r + \pi_i)t]$ for a portfolio of risky mortgages, while $V_i(0) = EV_i(t) \times \exp(-rt)$ in a risk-neutral setting where E is an expectation operator. If the default event is Bernoulli, the expected value, $EV_i(t)$, is given by $V_i(t) \times (1 - p_{iD}) + V_i(t) \times (1 - lgd) \times p_{iD}$, where p_{iD} is the probability of default from risk rating category i and lgd is loss given default. The risky and risk-neutral valuations must reconcile to prevent arbitrage, which implies the credit spread is $\pi_i = \ln(1 - lgd \times p_{iD})/t$.

U.S. Treasury bond data were used to find spot rates from which forward rates were calculated. These forward rates were then used in conjunction with the credit risk premiums to estimate one-year-forward yield curves to discount the mortgages' cash flows conditional on the transition from any risk rating category to any other risk rating category. Mortgages were priced on a per $100 of face-value basis. Once the one-year-ahead mean and standard deviation of the mortgage value was estimated, the moments were used to fit a beta distribution to the loan values from which the 5% VaRs could be determined.

The 5% VaRs are shown in Table 7 by risk rating class according to the method used to estimate the transition probabilities. For example, mortgages of the type described carrying a risk rating of 4 have a 5% VaR equal to $89.55 per $100 of face value irrespective of which transition probability estimates are used. The interpretation is that 5% of the time, we should expect the value of the mortgage to fall below $89.55 per $100 of face value given the likelihood of credit quality changes that may occur over one year.

In comparing the results, there is little difference between stationary MS and nonstationary MS VaRs since there was little difference in the estimation of the transition probabilities for the sample data. However, whether there is unobserved borrower heterogeneity in the sample matters for most of the other VaRs calculated. This is because the risk rating migration implied by the MS model suggests a lower probability of default than the maximum-likelihood estimates for a stationary first-order Markov chain.

For example, there is no statistical evidence that the VaR suggested by the stationary MS risk ratings migration matrix is lower than the VaR stemming from ML estimation for risk ratings 5–9. Recall, risk rating 9 offers compelling evidence of a high proportion of stayers. Therefore, there is a corresponding low probability of downgrade and/or default. This makes the VaR for the MS model very high relative to the VaR for the ML model since there is little to no risk of a downgrade or default.

Table 7. Comparison of Stationary Maximum Likelihood (ML) and Stationary (S) and Nonstationary (NS), Mover-Stayer, Entropy Transition Probabilities on 5% VaR

	Maximum Likelihood	Stationary Mover-Stayer Entropy		Nonstationary Mover-Stayer Entropy	
Risk Rating	5% VaR_{ML} ($)	5% VaR_S ($)	Prob($VaR_S \le VaR_{ML}$) (%)	5% VaR_{NS} ($)	Prob($VaR_{NS} \le VaR_S$) (%)
4	89.55	89.55	0.00	89.55	0.00
5	33.13	59.96	1.33	60.00	0.00
6	38.62	72.51	0.02	72.58	0.00
7	30.47	60.79	2.63	60.94	0.00
8	31.51	68.97	0.71	69.01	0.00
9	32.61	112.83	0.00	115.39	0.00
10	21.73	45.12	24.43	45.10	0.28
11	28.05	34.59	12.29	34.57	4.91
12	44.80	88.21	0.00	88.22	0.00

Note: Values reported are per $100 of face value assuming a 6.5% loan with a maturity of 20 years, a loss given default equal to 10%, and portfolio value fitted to a beta distribution.

With regard to risk rating classes 10 and 11, recall there was little empirical evidence of stayers in the sample and as a result, the MS VaR is much closer to the ML VaR. This finding implies that ignoring borrower heterogeneity could potentially cause AgChoice to hold much more capital in reserve than is actually necessary in an effort to manage an overstated level of credit risk in its portfolio.

Summary and Conclusions

In this article, we present a model for estimating credit risk rating migration matrices in the presence of unobserved heterogeneity—specifically, movers and stayers in the population of borrowers. Motivating the mover-stayer framework is the regular occurrence of obligors whose rating never changes due most likely to an exceptionally strong (or weak) financial position.

The approach is also flexible in a number of respects. First, if no such heterogeneity exists, the model collapses to a maximum entropy version of the familiar first-order Markov chain. Second, the entropy approach is sensitive to short time series which are nearly always problematic in studies of credit risk migration. Finally, the model can accommodate nonstationary transition probability estimation with minor adjustments to the moment consistency conditions.

We estimate risk migration matrices for a sample of Farm Credit System mortgages and do not find evidence of the trend reversals and momentum effects noted in previous research. We test for the order of the process and determine that for our data, risk ratings are not likely a second-order Markov chain. Similarly, past studies have concluded that the transition probabilities are nonstationary. We test this hypothesis and find no evidence, over the short span of our data, that nonstationary estimation is needed.

The mover-stayer model we estimate does, however, suggest the potential presence of borrower heterogeneity in our sample of loans. The most compelling evidence is for risk rating category 9, where perhaps a proportion as high as 97% of obligors were stayers over the sample period. If there is a high proportion of stayers in AgChoice's fixed-rate dairy loan portfolio, they are probably holding more than enough capital, since the risks of downgrade and default are likely overstated.

This result is consistent with past studies for corporate bonds where the presence of stayers has the effect of increasing the retention rates in the matrix and lowering the probability of default across risk classes. Consequently, the value-at-risk implied by transition probabilities estimated from our mover-stayer model indicates much higher values, and therefore would be suggestive of less capital needed to manage credit risk.

Further research is necessary to help determine whether borrower heterogeneity exists for other samples. In addition, past research should be revisited to clarify whether the trend reversals identified are the result of nonstationarity or simply a higher-order Markov process.

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Who Is Credit Constrained? Evidence from Rural Malawi

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Abstract

Using data from Malawi, this paper examines factors that influence a household's likelihood of facing credit constraints. We find that wealthier households are less likely to report credit constraints. Households with larger land holdings have a higher probability of reporting credit constraints, apparently due to lack of secure land rights which could enable households to use land as collateral when borrowing. Households with a greater number of active male adults are also more likely to report credit constraints.

Key words: credit constraints, elicitation, Malawi, rationing, sample selection

The general consensus among development experts is that the provision of financial services such as savings, credit, and insurance to low-income clients is a key element in pro-poor economic development. Through access to credit, households can diversify from low-risk/low-return investments to higher risk investments offering greater returns, thereby reducing their capital constraints (Diagne and Zeller, 2001; Jacoby, 1994).

However, as argued by de Janvry, Key, and Sadoulet (1997), lack of access to credit may not necessarily imply an unmet credit need. The authors note that credit access programs will be effective only to the "credit constrained"—i.e., those with access to productive investment opportunities who are unable to pursue these opportunities for lack of financial resources. Consequently, the poor without opportunities for productive investments may need to be targeted through publicly funded safety-net programs rather than credit programs. Thus, identifying who is credit constrained can lead to improvements in credit targeting and to the development of appropriate screening rules for credit applicants.

Exploring causes of credit constraints among the poor, Kritikos and Vigenina (2005) report that the reasons for the continued exclusion of the poor from financial markets contain a risk and cost component. It is difficult to determine the ability of the poor to repay the loan as well as their willingness to avoid moral hazard.[1]

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[1] Moral hazard in lending refers to situations where lenders cannot observe either the effort made or action taken by the borrower or the realization of the project returns.

Furthermore, as the loans required by the poor are generally quite small, the transaction costs to the financial institution associated with administering several small loans outweigh profits.

A key performance measurement of microfinance institutions is the extent to which they are able to reach the poor who have access to productive investment opportunities. Consistent with this notion, Zeller et al. (2006) contend that profitable microfinance institutions will not have served their original objectives if the poorest are not among their clients. Yet, as discussed above, the poorest may not demand credit due to lack of productive opportunities; therefore, targeting credit to those who have potential to efficiently utilize it requires some prior knowledge of these individuals' characteristics.

While the concept of credit constraints has been widely discussed in the literature, very little empirical investigation has been conducted on the characteristics of credit-constrained households. A few notable studies focusing on this topic include Jappelli (1990) who investigates the characteristics of credit-constrained households in the United States, and a study by Sawada et al. (2006) who examine the mother-child labor nexus under reported credit constraints among households from India. These studies are driven by strong assumptions that all households in a sample can be identified as either credit constrained or unconstrained. Here we argue that such identification may not always be possible, as the credit limit is unobservable.

Gilligan, Harrower, and Quisumbing (2005) attempted to estimate the determinants of credit constraints using a probit model in which the self-reported credit-constraint status is the dependent variable. However, we observe that the credit-constraint status of an individual is the net outcome of supply and demand for credit. Therefore, applying a simple probit estimation procedure may lead to biased estimates of the probability of being credit constrained as well as the determinants of this status because of the inability to accurately identify the credit-constraint status of all households in a sample.

This study is motivated by the concern that even well-designed credit programs will have limited or no impact at all if they fail to reach those who genuinely need credit. Our objective is to investigate the determinants of credit constraints and identify the key sources of such constraints. We seek to contribute to the credit literature by assessing determinants of credit constraints among a sample of households where the credit-constraint status is only observed conditional on asking for a loan.

The remainder of the paper is organized as follows. First, a review of methods used in identifying credit constraints is presented, including a discussion of the approach used in this study. The theoretical and empirical framework is then described, followed by a section devoted to an econometric specification of the empirical model. We next provide a description of the data and variables used in the empirical model. Our results and discussion are then highlighted and conclusions are presented in the final section.

Identification of Credit Constraints: A Review of Methods

A number of approaches are used to identify credit constraints in the literature. Such approaches fall into two categories—indirect methods and direct methods. Indirect methods are based on tests of theoretical models involving credit constraints while direct methods are based on responses to qualitative questions about credit-constraint status collected in surveys (Gilligan, Harrower, and Quisumbing, 2005).

The indirect methods involve comparisons of parameter estimates for specific outcomes across constrained and unconstrained groups. The most widely used models for indirect constraint tests include consumption smoothing models and farm labor demand models (Rosenzweig and Wolpin, 1993). Using a 1997 Peruvian data set collected by the World Bank, Vakis et al. (2004) propose what they call a superior approach for identifying credit-constrained households by adopting a mixture-distribution approach to estimate the probability that a farm household behaves according to nonseparability. Their findings show that the approach is quite reliable as it allows for the detection of nonseparability in a number of markets at once, and also allows for heterogeneity in separability behavior across households.

The direct method involves a direct elicitation in which respondents are asked questions about their perceptions of their credit-constraint status. Using survey questions that are usually qualitative in nature, respondents are asked about their current credit demand in order to identify households facing credit constraints.

The earliest application of this approach was carried out by Jappelli (1990). Japelli classified households in the U.S. 1983 Survey of Consumer Finances as credit constrained if they had a loan application rejected or did not apply for a loan because they believed they faced a probability of rejection. Feder et al. (1990) classified households in China as credit constrained if they stated their willingness to use more credit at prevailing interest rates if it were available. In a similar context, Diagne, Zeller, and Sharma (2000) classified a household as credit constrained if it had reached a perceived credit limit from any loan source or if its members stated they could not obtain credit. In general, all elicitation approaches rely on survey questions that identify whether or not a household's demand for credit exceeds the supply available to the household.

The demand for credit may exceed supply for credit for a number of reasons:

- First, the demand could exceed supply due to quantity rationing. Quantity rationing occurs when a lender sets credit limits that are lower than the household credit demand, usually resulting from moral hazard concerns and enforcement problems.

- Second, high transaction costs may also restrict the supply of credit to households. Jappelli (1990) observes that the existence of quantity constraints in credit markets can be explained by appealing to institutional constraints; thus for some consumers there may be no interest rate the banks are allowed to charge for which the bank's expected return is positive.

- Third, the demand for credit may exceed the supply for credit due to risk rationing.[2] Boucher, Carter, and Guirkinger (2005) define risk rationing as a condition that occurs when lenders, constrained by asymmetric information, shift so much contractual risk to the borrower that the borrower voluntarily withdraws from the credit market despite having the collateral wealth needed to qualify for a loan contract. The private and social costs of risk rationing are similar to those of more conventional quantity rationing. Like quantity-rationed individuals, risk-rationed individuals will retreat to lower expected return activities. Also, some individuals will avoid obtaining enough credit or never get credit at all due to fears of low returns on the investment. This will occur among risk-averse households who adopt a low-risk/low-investment strategy in order to avoid defaulting on the loan. However, potential borrowers may also withdraw from the credit market due to discouragement if they perceive their loan application will be rejected (Crook, 1999).

[2] Interested readers are referred to Boucher, Carter, and Guirkinger (2005) for further information.

There is a lack of consensus in the credit literature on "who is credit constrained." Specifically, there are those who argue that some rejected loan applicants and discouraged borrowers actually may not be credit constrained. Instead, they contend such households may be less creditworthy. For example, Getter (2002) shows that the rejection of low-credit quality borrowers or pricing them according to risk is consistent with well-functioning credit markets. This observation suggests the validation of credit constraints requires further information, including knowledge of the individual's credit history.

In this paper, our elicitation approach for identifying credit-constrained households depends solely on information from potential borrowers. First, we use households who applied for loans and were either turned down or not given as much credit as requested.

Second, following Jappelli (1990), we contend that applying for a loan is rarely costless; therefore, some potential borrowers may not apply for loans if they believe their applications will be rejected. In the credit literature these individuals are referred to as "discouraged borrowers." Omitting this group may lead to biased estimates of the probability that a household is credit constrained since the self-selection of applicants may induce intermediaries to adopt screening rules which differ from those that would prevail if the discouraged borrowers were to apply (Jappelli). Consequently, these households must be included in the analysis of the determinants of credit constraint.

However as noted by Jappelli (1990), the problem with including discouraged households in the sample of constrained households is that it may overstate the true number of constrained households—i.e., it may include those who wrongly believe their application will be declined. We also need to include within the group of discouraged borrowers those households who did not apply for credit for fear they would fail to repay the loan.

Accordingly, it is not possible to know with certainty whether a discouraged household is credit constrained, because we do not know if the household exceeds the maximum for which it is eligible from a lender. This designation is only observed once a household has asked for a loan and is rejected or rationed.

Theoretical and Empirical Framework

To obtain a precise definition of a credit-constrained individual and identify the determinants of credit constraints, we start by formulating an individual's optimization problem for the demand for credit as:

$$(1) \quad \max_{(\mathbf{x},b)\in S(\mathbf{z})} U(\mathbf{x}, b, \mathbf{z}),$$

where $U(\cdot)$ is the objective utility function, b is the credit amount choice variable (loan size), and $\mathbf{x}$ is the vector of other choice variables.

$S(\mathbf{z})$ represents the constraint set which defines the set of feasible household choices, where $\mathbf{z}$ is the vector of all non-choice variables that affect the objective function U and the constraint set $S(\mathbf{z})$ (including household sociodemographic variables, prices, technological, and other variables that condition household choices).

If the constraint set $S(\mathbf{z})$ does not include any constraint on the amount b the household can borrow, then the household optimal choice for credit $b(\mathbf{z})$, as given by equation (1), defines the household *latent* credit demand—i.e., the amount the household would like to borrow if there were no limit on the amount it could borrow.

However, because there is always a limit to the amount one can borrow, let b_m be the household's credit limit (the maximum amount the household can borrow). This means that in addition to the constraint set $S(\mathbf{z})$, the household faces a credit constraint of the form $0 \le b \le b_m$, and the amount it receives when asking for a loan is given by:

$$(2) \quad b^* = \min\left(b(\mathbf{z}),\, b_m\right).$$

Note that the actual credit borrowed, $b^* \equiv \min(b(\mathbf{z}), b_m)$, can be observed only if the potential borrower has asked for a loan. So, letting $D = 1$ if the household asks for a loan, and $D = 0$ otherwise, the *observed* loan received is expressed as:

$$(3) \quad b = \begin{cases} b^* = \min\left(b(\mathbf{z}),\, b_m\right) & \text{if } D = 1, \\ 0 & \text{if } D = 0. \end{cases}$$

Therefore, $b = Db^*$. This implies that in reality credit demand can be observed only among households who have requested a loan.

Following Diagne and Zeller (2001), we use the credit limit variable b_m to define access to credit. A household is said to have access to credit if b_m is strictly positive; otherwise (i.e., if $b_m = 0$) it is said to have no access to credit. The extent of household access to credit is measured by the magnitude of b_m. It is important to note that access to credit is purely supply driven, as b_m is wholly determined by lenders (based on information about the potential borrower's repayment ability and the credit market).

We also use the credit limit and latent credit demand to formally define what is meant by a credit-constrained household. A household is said to be *credit constrained* when $b(\mathbf{z}) > 0$ and $b(\mathbf{z}) > b_m$ (i.e., the household wants to borrow but cannot borrow as much as it wants). So if we denote by C the credit-constraint status indicator (with $C = 1$ indicating being credit constrained), we have:

$$(4) \quad C = \begin{cases} 1 \text{ if } b(\mathbf{z}) > 0 \text{ and } b(\mathbf{z}) > b_m, \\ 0 \text{ if } b(\mathbf{z}) = 0 \text{ or } b(\mathbf{z}) \le b_m. \end{cases}$$

The above definition of credit constraint implies that a household is *not* credit constrained if it has no demand for credit [i.e., $b(\mathbf{z}) = 0$], regardless of whether or not it has access to credit. Note, while access to credit is purely supply driven, depending only on the value of b_m, being credit constrained is supply *and* demand driven because it depends on the values of both b_m and $b(\mathbf{z})$. Furthermore, since access to credit is independent of credit demand, a household may or may not have access to credit regardless of its credit demand.

It can be argued that credit limits are not known to households because these limits are determined by lenders. A potential borrower can only form expectations about his or her credit limit b_m from a lender, and the borrower may have the chance to learn its true value only when s/he asks for a loan from the lending source (Diagne and Zeller, 2001). Moreover, even when a potential borrower requests a loan, s/he may not be informed of the credit limit if s/he is given the loan amount requested. Therefore, the credit limit variable b_m is not always known when information is obtained from borrowers only.

Because b_m is not observed, we cannot use knowledge of its value to determine whether or not we have $b(\mathbf{z}) > b_m$, except when the latent credit demand $b(\mathbf{z})$ is known to be zero. Hence, we cannot rely on knowledge of the credit limit b_m to determine if a household is credit constrained, except when the household is known to have no demand for credit (in which case it is, by definition, not credit constrained). Even when a loan is requested and we observe the actual loan received, $b^* = \min(b(\mathbf{z}), b_m)$, it still cannot be determined whether or not the household is credit constrained except when $b^* = 0$ (i.e., when the loan demand is rejected).

Note, however, the determination of a household's credit-constrained status does not require exact knowledge of the values of b_m and $b(\mathbf{z})$. All that is required is knowledge of whether or not $b(\mathbf{z}) > b_m$ (i.e., the value of the binary indicator variables $1_{[b(\mathbf{z}),\, b_m]}$) or whether or not $b(\mathbf{z}) = 0$.

Nevertheless, this information can be partially inferred from information about the household's credit market participation outcomes pertaining to (*a*) whether the household has asked for a loan, (*b*) the household's reasons for not asking for a loan if it has not requested credit, and (*c*) whether the household has received the full amount requested if it has asked for a loan.

Information pertaining to (*a*) will tell us the value of D (0 or 1). If $D = 1$, then we know that $b(\mathbf{z}) > 0$ (i.e., since the process of asking for a loan is rarely costless, only households who have a latent credit demand will ask for a loan). Also, if $D = 1$ and either the observed loan received $b^* = 0$ (i.e., the loan demand was rejected), or the information pertaining to (*c*) tells us that the household has not received as much as it wanted, then we can infer $b(\mathbf{z}) > b_m$. That is, the household is credit constrained (i.e., $C = 1$). Otherwise (i.e., $D = 1$ and $b^* > 0$, and the household has received the full amount it requested), we can infer from (*c*) that $b(\mathbf{z}) \leq b_m$, indicating the household is not credit constrained (i.e., $C = 0$).

On the other hand, if $D = 0$, either one of the two cases [$b(\mathbf{z}) > 0$ or $b(\mathbf{z}) = 0$] is possible. Which of the two possible cases is realized can sometimes be inferred from information pertaining to (*b*) if the reasons given by the household for not asking for a loan translate to no demand for credit, i.e., $b(\mathbf{z}) = 0$ (this is the case, for example, when the household states "I don't want/need a loan" or "I don't like borrowing"). In this situation [when $D = 0$ and $b(\mathbf{z}) = 0$], the household is not credit constrained by definition. Otherwise, when the information pertaining to (*b*) points to the case $b(\mathbf{z}) > 0$ (e.g., the case of the "discouraged borrowers"), then the credit-constrained status of the household cannot be determined.

Thus, households who did not apply for a loan due to reasons other than lack of demand for credit cannot be identified as either credit constrained or unconstrained. It is difficult to identify these households because although they exhibit a positive demand for a loan $b(\mathbf{z}) > 0$, we are unable to tell if the demand exceeds their credit limit [$b(\mathbf{z}) > b_m$ or $b(\mathbf{z}) < b_m$] since the values of both b_m and $b(\mathbf{z})$ are unknown.

Figure 1 shows a flowchart presentation of the classification of households based on their responses to these questions. The definition of being credit constrained and the methodology for identifying credit-constrained households are as described above.

The preceding arguments suggest we can only identify credit constraints with precision among households who apply for credit. Furthermore, our definition of C is that it is a function of both demand $b(\mathbf{z})$ and supply b_m. Therefore, to consistently identify determinants of credit constraints, a model is required that considers the potential problem of endogeneity. To address the endogeneity problem, we adopt the instrumental variable approach (with participation in a credit program as an instrument). Participation in a credit program is assumed to be a valid instrument of the model because participation is expected to affect the likelihood of asking for a loan but does not directly affect credit-constraint status.

Following Hayashi (1985), Jappelli (1990), and Sawada et al. (2006), we assume the reduced form of the credit-constraint status of a household conditional on asking for a loan can be explained by the same factors that influence the household's demand for and access to credit, such as the household's human and physical assets.

Therefore, in the empirical section below, determinants of being credit constrained are estimated conditional only on loan application. Specifically, we estimate the model $\text{Prob}(C = 1 \mid \mathbf{X}, D = 1)$, where $\mathbf{X}$ is a vector of household and credit market characteristics that determine the household's status of being credit constrained or unconstrained.

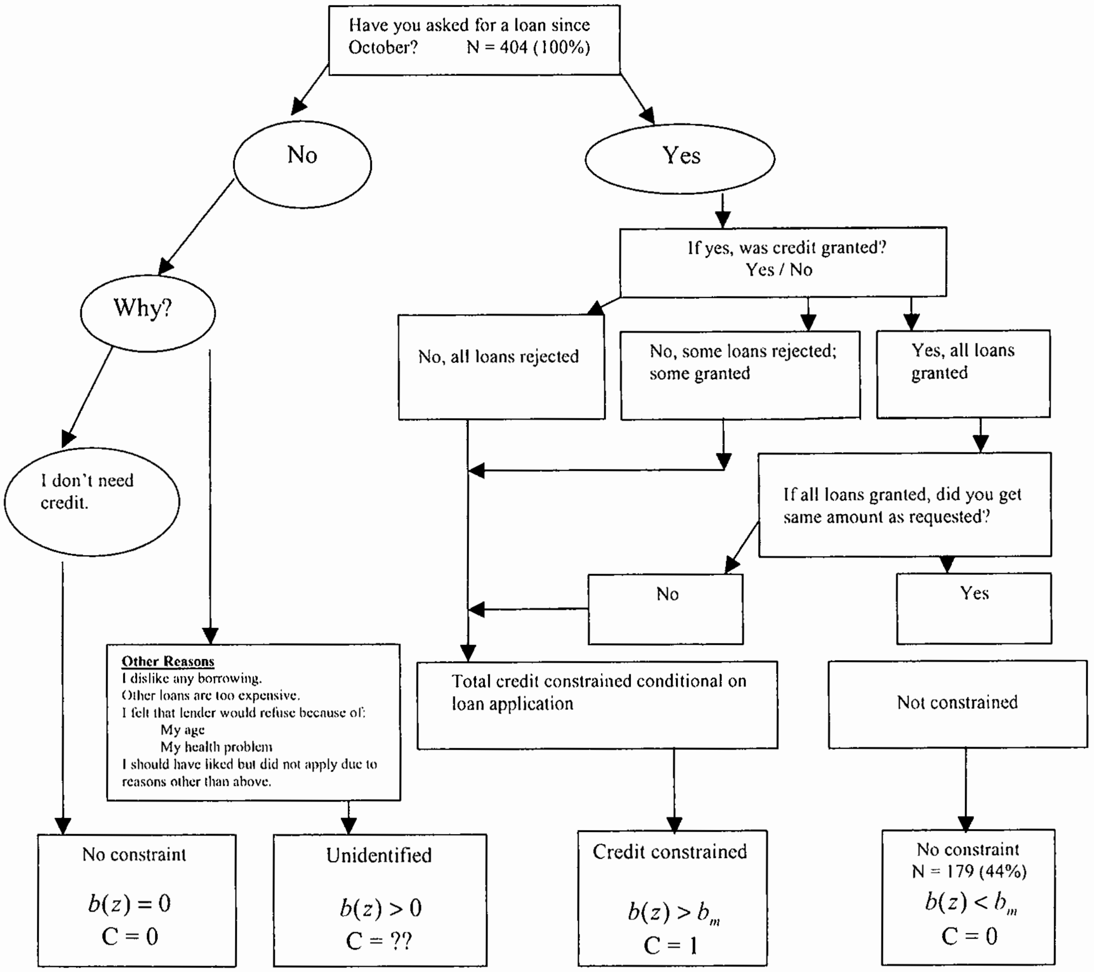

Figure 1. Flowchart Showing Identification of Credit Constraints

For this study we used the data collected by the International Food Policy Research Institute (IFPRI) in Malawi in 1994, which contains the information needed for identification of credit-constrained households using the methodology described above. Although the data set is somewhat dated, and some conditions in Malawi in 2008 could be different from those occurring in 1994, to a large extent the poverty levels and the levels of access to financial services by the poor have mostly remained the same. While our aim is to assess current conditions, it is helpful to use a well-established survey to illustrate how one could ultimately measure credit constraints.

In the IFPRI survey, respondents were asked whether or not they had tried to borrow from a formal lender in the past 12 months. Those who had requested loans were asked the amount they received and whether they received the full amount requested. Respondents who had not attempted to borrow were asked their reasons for not doing so. Specifically, the questions were as follows:

1a. Did any member in your household apply for a loan from a formal institution in the last 12 months? [Yes / No]

1b. If your household applied, was the loan granted? [Yes / No]

1c. If the loan was granted, was the household granted the same loan amount as requested? [Yes / No]

2. If household members did not attempt to borrow, please give reasons. [Select from the choices below.]

   1) = I did not need credit.

   2) = I dislike any borrowing.

   3) = The loans are too expensive.

   4) = I would have liked to apply for a loan but did not apply because I felt the lender would not give me a loan because of my age.

   5) = I would have liked to apply for a loan but did not apply because I felt the lender would not give me a loan because of my health problems.

   6) = I would have liked to apply for a loan but did not apply because I felt the lender would not give me a loan for reasons other than age and health problems.

   7) = Other reasons [please list]

Respondents who chose any of options 3, 4, 5, and 6 as reasons for not attempting to obtain a loan from a formal institution are categorized as discouraged borrowers. In much of the credit literature, households choosing options 3–6 are classified as credit constrained. But as discussed earlier, the credit-constrained status of these households cannot be accurately determined based solely on the information above.

Econometric Specification of the Empirical Model

To estimate the model of the determinants for being credit constrained [$\text{Prob}(C = 1 \mid \mathbf{X}, D = 1)$ as described above], we employ the binary response model with sample selection framework (Gronau, 1974; Heckman, 1976). For this procedure, we use parametric specifications for the determinants of credit market participation and being credit constrained as given above by equations (3) and (4):

(5) $D = 1[\mathbf{z}\boldsymbol{\delta} + \boldsymbol{\mu} > 0]$,

(6) $C = 1[\mathbf{x}\boldsymbol{\beta} + \boldsymbol{\varepsilon} > 0]$,

where $1[\cdot]$ is the set indicator function; $\mathbf{x}$ and $\mathbf{z}$ are the vectors of (explanatory) household socioeconomic credit market characteristic variables that determine credit market participation and credit-constrained status, respectively; $\boldsymbol{\beta}$ and $\boldsymbol{\delta}$ are vectors of parameters to be estimated; and $\boldsymbol{\mu}$ and $\boldsymbol{\varepsilon}$ are unobserved error terms, where $\boldsymbol{\mu} \sim N(0, 1)$, $\boldsymbol{\varepsilon} \sim N(0, 1)$, and $\text{corr}(\boldsymbol{\mu}, \boldsymbol{\varepsilon}) = \rho$.

Hence, it is assumed that the unobserved error vector $(\boldsymbol{\mu}, \boldsymbol{\varepsilon})$ is distributed bivariate normal with zero mean and independently to the explanatory variables $\mathbf{z}$ and $\mathbf{x}$. Equation (5) is the selection equation explaining credit market participation ($D = 1$ if an individual asked for a loan), and equation (6) is the credit-constrained equation, the outcome equation in which the dependent variable is observed only when $D = 1$.

The conditional probability $[\text{Prob}(C = 1 \mid \mathbf{X}, D = 1)]$ derived from equations (5) and (6), which we estimate as a probit model with sample selection, and its estimation is discussed in detail in Wooldridge (2002, pp. 570–571) (see also the *heckprob* command in the STATA 10.0 reference manual, pp. 570–572). According to Wooldridge (p. 571), a convincing identification of this model that does not rely purely on its nonlinearity requires at least one variable in $\mathbf{z}$, i.e., a variable that determines selection (in this case credit market participation) and which is not included in the outcome equation (status of being credit constrained). In our analysis we include membership in a credit program as the instrument.

We hypothesize that the credit membership program has an influence on the likelihood of asking for a loan, but since the individual borrower cannot choose the credit limit, membership may not directly affect the credit-constraint status. Thus, apart from the program membership variables which only appear in the selection equation as instruments, other variables may appear in both equations. This approach corrects for the possible sample selection bias that could result from estimating determinants of credit constraints solely on a restricted sample of households who asked for a loan. The model is estimated using the *heckprob* command in STATA version 10.0.[3]

[3] Using STATA 10.0, the command *heckprob* can be used to calculate a bivariate probit model with sample selection through a maximum-likelihood estimation process.

Description of Data and Variables Used in the Empirical Model

Although the microfinance sector in Malawi is still small, it is growing rapidly. Financial services to micro enterprises and low-income households in Malawi are provided by a wide variety and range of private and publicly supported microfinance institutions consisting of NGOs, companies limited by guarantee, savings and credit cooperatives, and commercial banks, including one bank specializing in microfinance.

Description of Data

The data used in this analysis are drawn from a survey of households conducted by the International Food Policy Research Institute (IFPRI) and the Department of Rural Development at Bunda College of Agriculture in Malawi in 1996. The survey was designed to investigate the effects of access to credit on household welfare. The survey covered 404 households, selected via the stratified random sampling method, from Malawi's southern, central, and northern regions which include the five districts of Rumphi, Nkhotakota, Dowa, Dedza, and Mangochi.

The four microcredit programs that were the focus for the IFPRI survey included the Malawi Rural Finance Company (MRFC), a state-owned and nationwide agricultural credit program; Promotion of Micro-Enterprises for Rural Women (PMERW), a microcredit program targeted at women in support of nonfarm income-generating activities; the Malawi Mudzi Fund (MMF), a replica of the Grameen Bank; and the Malawi Union of Savings and Credit Cooperatives (MUSCCO), a union of locally based savings and credit associations. With the exception of MUSCCO, all programs rely on group lending.

The IFPRI survey focused on these four microfinance institutions as representative of the spectrum of formal credit and savings options available to rural

Table 1. Household Statistics Showing Credit Application Status, with Reasons Cited for Nonapplication

Description	Credit Application Status: Households Who Applied for Credit	Credit Application Status: Households Who Did Not Apply for Credit	Total
No. of households by credit category	275 (68%)	129 (32%)	404
No. of respondents w/loans rationed or rejected	96 (34%)	0	96 (24%)
No. of respondents who received full loan amount	179 (66%)	0	179 (44%)
Respondents' reasons for not applying for credit:			
▸ Do not need any credit.		29 (23%)	29 (7%)
▸ Credit is expensive, or dislike borrowing for fear of repayment failure		23 (17%)	23 (6%)
▸ Discouraged for fear the lender would reject the loan due to age or poor health reasons		18 (15%)	18 (4%)
▸ Discouraged for fear the lender would reject the loan for other reasons		22 (17%)	22 (5%)
▸ Reasons other than those cited above		29 (23%)	29 (7%)

Source: Authors' calculations from Malawi-IFPRI survey.

households in Malawi. The data were collected from members of credit programs as well as nonprogram members.

The sample included 404 households, half of which were members of the credit programs and the other half nonmembers. Respondents were asked a number of questions related to socioeconomic and demographic characteristics. They were also asked to provide information about their credit participation and whether they had requested any loan within the past 12 months. Because this study examines access to formal credit, our definition of credit constraint is with respect to the formal credit market.

Table 1 provides statistics for households who applied for credit and those who did not, as well as the reasons cited for nonapplication for credit. Results indicate 68% of the households reported they had asked for a loan. Of those, 66% reported they had been granted the full amount requested, while 34% stated they had not. The latter constituted a group of credit-constrained households. For those households who did not apply for credit, 23% indicated they did not need credit, while 17% cited the cost of borrowing and a general dislike of borrowing as the reason they did not ask for a loan. Furthermore, 15% stated they did not ask for credit because they felt the lender would deny them a loan due to their age or poor health. Approximately 17% of households were discouraged from asking for a loan for other reasons, and 23% cited reasons other than discouragement as their explanation for not requesting a loan.

Table 2 reports household characteristics disaggregated by whether or not a household had asked for a loan. Those who requested a loan have significantly larger households (5.9 persons) than those who did not ask for credit (4.6 persons). There are significantly more adult males and females among households asking for credit compared to those who did not. This finding is not surprising considering that households with more adults have a greater likelihood of participating in credit programs than those with fewer adults.

Respondents asking for credit are relatively older (46.2 years) than those who did not (42.8 years) and also have larger land holdings (2.15 hectares) than their

Table 2. Household Characteristics (means), Disaggregated by Whether or Not the Household Asked for a Loan (credit-market participation)

	Credit Application Status		
Characteristic	**Households Who Applied for Credit (n = 275)**	**Households Who Did Not Apply for Credit (n = 129)**	**Total (n = 404)**
Age of household head (years)	46.23	42.79*	45.13
	(12.30)	(15.78)	(13.58)
Household size (number of persons)	5.94	4.57	5.51
	(2.37)	(2.43)	(2.47)
Years of education of household head	4.32	4.20	4.28
	(3.30)	(3.35)	(3.31)
Gender of household head (1 = male; 0 = otherwise)	0.75	0.66*	0.72
	(0.43)	(0.48)	(0.45)
Population of males aged 15–64 years	1.33	1.00*	1.22
	(0.93)	(0.76)	(0.89)
Population of females aged 15–64 years	1.56	1.29**	1.47
	(0.81)	(0.79)	(0.81)
Total household land area (hectares)	2.15	1.76*	2.03
	(1.90)	(1.99)	(1.93)
Asset value (Malawi kwachas)[a]	3,579.09	3,417.60	3,527.00
	(6,844.00)	(11,802.00)	(8,723.00)
Distance to commercial bank (kilometers)	34.47	35.22	34.71
	(19.45)	(19.72)	(19.52)
Maximum formal loan size possible (Malawi kwachas)	217.23	9.50	148.18
	(709.80)	(65.29)	(589.00)

Source: Authors' calculations from Malawi-IFPRI survey.

Notes: Single, double, and triple asterisks (*) denote statistical significance of difference in means at the 10%, 5%, and 1% levels, respectively. Values in parentheses are standard deviations.

[a] At the time of the IFPRI survey in 1994, one U.S. dollar was the equivalent of 44 Malawi kwachas.

counterparts who did not ask for credit (1.76 hectares). Furthermore, a much smaller proportion of female-headed households (25%) had at least one member asking for a loan compared to households not requesting credit (34%), suggesting participation in credit markets has a "gender face," as more male-headed households ask for credit than female-headed households. Our results reveal no marked differences in most of the other household characteristics.

Focusing on those households who asked for a loan, we further disaggregate them according to whether they were granted the full loan amount requested. Results in Table 3 indicate there are more male-headed households in the rationed group (81%) than in the group of households who were granted the full amount of loan requested (72%). Credit-constrained households have more adult males (1.49 persons) than nonconstrained households (1.25 persons). Credit-constrained households have larger land holdings (2.52 hectares) compared to their nonconstrained counterparts (1.95 hectares). This finding appears to suggest that because of their larger land holdings, credit-constrained households are more likely to request a larger amount of credit for their productive activities on the land, thus driving demand to exceed their credit limit (b_{max}).

Table 3. Household Characteristics (means) of Credit Applicants by Whether or Not They Were Credit Constrained (conditional on asking for a loan)

Characteristic	No Credit Constraint (unconstrained) (n = 179)	Credit Constrained (rationed) (n = 96)	Total (n = 275)
Age of household head (years)	45.96	46.73	46.23
	(12.26)	(12.43)	(12.30)
Years of education of household head	4.31	4.34	4.32
	(3.30)	(3.31)	(3.30)
Gender of household head (1 = male; 0 = otherwise)	0.72	0.81*	0.75
	(0.45)	(0.39)	(0.43)
Population of males aged 15–64 years	1.25	1.49**	1.33
	(0.87)	(1.02)	(0.93)
Population of females aged 15–64 years	1.59	1.50	1.56
	(0.81)	(0.81)	(0.81)
Total household land area (hectares)	1.95	2.52**	2.15
	(1.13)	(2.78)	(1.90)
Per capita land size (hectares)	0.40	0.47	0.42
	(0.30)	(0.44)	(0.36)
Asset value (Malawi kwachas)	3,132.27	4,412.22	3,579.09
	(5,769.59)	(8,466.65)	(6,844.91)
Distance to commercial bank (kilometers)	33.56	36.15	34.47
	(18.09)	(21.75)	(19.45)
Maximum formal loan size possible (Malawi kwachas)	186.54	299.55	217.23
	(335.89)	(1,249.41)	(709.84)

Source: Authors' calculations from Malawi-IFPRI survey.

Notes: Single, double, and triple asterisks (*) denote statistical significance of difference in means at the 10% and 5% levels, respectively. Values in parentheses are standard deviations.

Variables Used in the Empirical Model

Variables and their expected impact on the household's likelihood of asking for a loan (demand), supply of credit, and the credit-constraint status are presented in Table 4.

We expect that both the demand and supply of credit to a household will increase with the age of a household head. Demand for credit increases as a response to the rise in the size of investments made by households as they grow older. When lenders consider age as an indicator of experience, it is likely that access to credit will also increase with age. Therefore, the impact of age on the probability of being credit constrained will depend on the magnitude of the two opposing outcomes and cannot be predetermined.

Education of a household head can have a positive effect on demand for credit if education leads households to acquire the necessary skills for managing larger investments that will require more credit. On the supply side, education may have competing effects. First, it can have a positive effect if it is used as an indicator of productivity, and thus lenders may be willing to lend more to educated people with the expectation that the risk of default is much lower. Second, education might have a negative effect if credit programs are pro-poor in focus and target the poor and illiterate individuals. Thus, the net effect of education on the probability of being credit constrained cannot be predetermined.

With regard to gender, we hypothesize that male-headed households will demand

Table 4. Expected Effects of Specific Characteristics on Credit-Constraint Status

Characteristic		Asking for a Loan/Demand	Supply of Credit/Access	Probability of Being Credit Constrained
Age of household head		+	+	+ / –
Years of education of household head		+ / –	+	+ / –
Gender of household head		+ / –	+ / –	+ / –
Number of adult males (> 15 years)		+ / –	+ / 0	+ / –
Number of adult females (> 15 years)		+ / –	+ / 0	–
Value of Assets:	Quartile 1	–	–	+ / –
	Quartile 2	–	–	+ / –
	Quartile 3	+ / –	+ / –	+ / –
	Quartile 4	+	+	+ / –
	Quartile 5	+	+	+ / –
Membership in a credit program		+ / –	+ / –	+ / –
Total household land area		+	+	+ / –
Distance to commercial bank		0	–	+

more credit than female-headed households because male-headed households also have greater access to other production resources requiring credit supplementation compared to female-headed households. On the supply side, however, we expect female-headed households will have more access to credit because most microfinance institutions in the rural communities have a gender bias toward women. Given that male-headed households may also be capable of self-financing, it is not possible to predetermine the expected impact of gender on the probability of being credit constrained.

As noted by Gilligan, Harrower, and Quisumbing (2005), the number of adults in a household increases demand for credit for consumption but reduces demand for farm labor if factor markets are imperfect. However, the presence of more adults in a household could imply that a household has more income earners, thereby increasing its capability of self-financing and leading to reduced credit demand. On the supply side, a larger number of adults in a household implies more potential borrowers and thus increases credit supply. The overall effect on credit-constraint status is ambiguous. In order to capture the impact of gender, we therefore separate the counts of adults into males and females.

The wealth of the household is captured by five ranks (quartiles) of household wealth based on the asset value. We expect that poor households will have less demand for credit, while their access to credit may be increased due to the poverty lending programs that target the poor. As such, the net impact on the household credit-constraint status is not predetermined.

The size of cultivable land and its square is included as an indicator of demand for credit arising from the demand for production inputs. Thus, we expect total household land area will have an increasing effect on demand for credit, and we therefore predict that the probability of being credit constrained will increase with land size. Finally, distance to commercial centers increases the probability of a household being credit constrained by raising transaction costs of obtaining loans.

Results and Discussion: Determinants of Credit Constraints

The maximum-likelihood estimates from a Heckman probit of the determinants of credit constraints are presented in Table 5. Given that the estimated coefficients reflect the effect of independent variables on the odds of the probability rather than the probability itself, we report the marginal effects of the probability that a household participating in credit markets faces credit constraints. The model χ^2, which measures the goodness of fit of the model, is significant at the 1% level, signifying a good fit.

Consistent with observations reported by Jappelli (1990), the coefficient for the number of adult and active male members per household (aged 15–64 years) is positive and significant at the 5% level, indicating households with more adult male members have a greater likelihood of facing credit constraints than those with smaller numbers of male members. Results reveal that adding one more adult to a household increases the probability of facing credit constraints by 7.8%.

As suggested by these findings, households with abundant labor are more likely to ask for loan amounts higher than their credit limit. This is consistent with the observation by Gilligan, Harrower, and Quisumbing (2005) who noted that the number of adults in a household increases demand for credit, but reduces demand for farm labor if factor markets are imperfect. Furthermore, in this study we considered loan applications for all adult members in the household, and if any single member of a household had his or her loan rejected or rationed, that household was considered to be credit constrained. Therefore, the probability of having at least one loan rejected is likely to be high among households with more adults than among households with fewer adults (i.e., fewer potential loan applicants).

The proxy variables for wealth returned expected signs. The coefficients for the third, fourth, and fifth quartiles of the value of household nonagricultural assets are negative and significant at the 5%, 10%, and 5% levels, respectively. These findings suggest that wealthier households in the third, fourth, and fifth quartiles are less likely to face credit constraints. The probability of reporting credit constraints declines by approximately 12–14% in each of these three wealth categories—consistent with prior expectations that wealthier households are more likely to have the ability to self-finance, thus reducing the demand for credit. Our results are also consistent with observations reported by Zeldes (1989) and Hayashi (1985) who found constrained households are likely to have little wealth. Jappelli (1990) also concludes that wealthier households in the United States are less likely to report credit constraints.

The coefficient for the total household land area is positive and significant at the 5% level, suggesting households with larger holdings are more likely to report credit constraints. Increasing land holdings by one hectare increases the likelihood of reporting credit constraints by 16%. This finding is not entirely surprising, since households with large land holdings may demand credit in an amount exceeding their credit limit. These results are also consistent with prior expectations—i.e., most land in Malawi is held under customary ownership, and so households have limited rights over it. Under the customary law, a household only has the right to use the land but does not own it; therefore, title deeds are not available in communal areas. This, in addition to the fact that customary land can be transferred from one household to another by the traditional leaders, reduces the value of land. It follows that households cannot use land as collateral for accessing loans from a lending institution. Clearly, this is a cause for concern when considering that several studies (e.g., Kaakunga and Ndalikokule, 2006; Field and Torero, 2005) conclude that well-secured property rights can improve access to credit by the poor.

Table 5. Determinants of Credit Constraints: Heckman Probit Maximum-Likelihood Estimates

Constraint Equation		**Asking for a Loan**	**Credit Constraint**	**Marginal Effects (dy/dx)**
Age of household head		0.0062	0.0058	0.0021
		(0.0055)	(0.0074)	(0.0020)
Years of education of household head		-0.0158	0.0090	0.0008
		(0.0306)	(0.0326)	(0.0090)
Gender of household head (male = 1)		0.0756	0.2417	0.0697
		(0.1787)	(0.2200)	(0.0575)
Number of adult males (> 15 years)		0.1534	0.2342**	0.0777**
		(0.1050)	(0.0930)	(0.0271)
Number of adult females (> 15 years)		0.1360	-0.0540	-0.0164
		(0.1114)	(0.1182)	(0.0332)
Value of Assets:	Quartile 2	0.3175	-0.3930	-0.0776
		(0.2100)	(0.3021)	(0.0755)
	Quartile 3	0.4225*	-0.5970**	-0.1200*
		(0.2433)	(0.3030)	(0.0687)
	Quartile 4	0.3618	-0.6010*	-0.1240*
		(0.2516)	(0.3256)	(0.0732)
	Quartile 5	0.3150	-0.6700**	-0.1418*
		(0.2995)	(0.3317)	(0.0719)
Total household land area (hectares)		-0.0559	0.6282**	0.1636**
		(0.2155)	(0.2464)	(0.0716)
Distance to commercial bank		-0.0129	-0.0070	-0.0320
		(0.0131)	(0.0159)	(0.0045)
Districts:	Mangochi	0.0809	0.2309	0.0723
		(0.7237)	(0.8747)	(0.2664)
	Nkhotakota	0.3620	-0.0154	0.0271
		(0.4517)	(0.5282)	(0.1560)
	Rumphi	-0.1532	-0.8500**	-0.2009***
		(0.3251)	(0.3354)	(0.0635)
	Dedza	0.1809	-1.4150***	-0.2869***
		(0.3285)	(0.4040)	(0.0638)
Microcredit Program Member:	MRFC	1.4212***		0.0972**
		(0.2511)		(0.0638)
	MMF	1.8267**		0.0833
		(0.4330)		(0.0481)
	MUSCCO	1.1308***		0.0693**
		(0.3993)		(0.0374)
	PMERW	1.3124***		0.0837*
		(0.2887)		(0.0427)
Constant		-0.6346	-0.2629	
		(0.4663)	(0.5966)	
Rho		0.0526		
		(0.3049)		

Number of observations = 404
Censored observations = 129
Wald χ^2 (15 df) = 54.36***
Log pseudo-likelihood = -336.7683
Wald test of independent equations (rho = 0): χ^2 (1 df) = 0.03, Prob > χ^2 = 0.8524

Source: Authors' calculations from Malawi-IFPRI survey.

Notes: Single, double, and triple asterisks (*) denote statistical significance at the 10%, 5%, and 1% levels, respectively. Values in parentheses are standard errors.

Conclusion and Policy Implications

The current policy emphasis on credit as a development tool, coupled with the limited availability of poverty funds for credit, highlights the importance of targeting credit to those who truly need it. Specifically, credit-constrained households need to be given access to productive investment opportunities.

We have investigated the occurrence of credit constraints among households from rural Malawi, and our findings reveal that approximately 24% of households who had asked for credit were credit constrained. Due to our assumption that the credit-constraint status of a household is known only conditional on loan application, we adopted a Heckman's correction procedure to estimate determinants of credit constraints. In order to minimize the endogeneity problem, the instrumental variable approach (with credit program participation as an instrument) was used to address endogeneity.

Results indicate that the wealth of a household reduces the probability of being credit constrained. The policy implication for this finding is that credit, and indeed any safety-net program aimed at reducing liquidity constraints among rural clientele, would be more effective if targeted toward a certain category of households, such as the poor with less assets.

Still, any pro-poor credit policy would need to be carefully formulated because, as noted by Getter (2002), sometimes liquidity constraints may be an indication of a household's incapacity to service the loan. Such households would need to be targeted with other forms of safety-net programs, such as the free-input distribution programs or the subsidy program currently being implemented by the government of Malawi. We note that since 1994 when the data were collected, the government of Malawi has been implementing such safety-net programs, including the Targeted Input Programs (TIPs) from 1998 (Gough, Gladwin, and Hildebrand, 2001) whose major objective is to provide free agricultural inputs to the poorest households lacking the means for financing the purchase of agricultural inputs.

However, based on the data used in this study, it was not possible to assess the capacity among rejected and discouraged households to service loans, and therefore their credit-constraint status cannot be fully identified. Any future studies examining credit constraints could make a significant contribution to the credit literature if they also administer questions of credit and repayment history as well as questions designed to capture the ability to service a debt among rejected, rationed, and discouraged borrowers. Such an approach could improve on the precision of identifying whether or not a household is credit constrained.

Furthermore, we find that the probability of facing credit constraints increases with landholding size, apparently due to lack of secure property rights among rural communities. As reported by Field and Torero (2005), there is a strong theoretical link among credit access, property rights, and economic development; strengthening property rights encourages lenders to accept land as collateral, thereby reducing credit rationing in financial markets. There is a clear need for the revision of Malawi's customary law in a way that rural communities can lease their land and subsequently use the lease agreement as collateral to secure loans from lending institutions for agricultural production purposes. Such lease agreements must ensure that the lending institutions are empowered to repossess the land for resale in the event of repayment failure.

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Dynamic Incentive with Nonfinancing Threat and Social Sanction in Rural Credit Markets

Kien Tran Nguyen and Makoto Kakinaka

Abstract

This paper analyzes an individual lending credit market in a rural society, where potential borrowers have a dynamic incentive of strategic default, and a benevolent lender gives them a credible threat to cut future credit when loans are not repaid. A crucial issue is that social sanction of default depends on the default rate in the society. Our analysis suggests that for a relatively small financing cost, a credit market exists where borrowers have little motivation to default voluntarily, associated with intense social sanctions. The results also reveal that a relatively large financing cost causes the credit market to collapse, since it raises motivation of default, associated with less intense social sanctions. These results could justify government support to reduce the lender's financing cost. The model further illustrates the plausibility of two equilibria: a low default rate associated with a low lending rate and intense social sanctions, and a high default rate with a high lending rate and less intense social sanctions. This could explain the possibility that the default rate is different from village to village even though these societies seem to share an almost identical environment.

Key words: asymmetric information, dynamic incentive of strategic default, endogenous social sanction, nonfinancing threat, rural credit market

Rural credit markets in developing economies often suffer from adverse selection and moral hazard problems, although various market structures, such as peer monitoring and group lending, with various government supports have been established to address these issues.[1] Since securing high repayment rates is a crucial determinant of lenders' sustainability, a credible threat to cut any future credit when loans are not repaid has been identified as an important mechanism to mitigate borrowers' dynamic incentive to default (see, e.g., Hulme and Mosley, 1996; Morduch, 1999; Armendariz de Aghion and Morduch, 2000; Chowdhury, 2005; Tedeschi, 2006).

At the same time, several researchers emphasize that social sanctions associated with a high degree of social connectedness may also constitute an effective device to avoid the issue of strategic default (see, e.g., Besley and Coate, 1995; Wydick, 1999). Given these arguments, this paper seeks to examine the relation among the lending rate, the default rate, and social sanctions in a rural society.

Voluntary default is pertinent in the context where the legal system of loan enforcement is weak. In most developing

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[1] See Ghatak and Guinnane (1999); Morduch (1999); and Armendariz de Aghion and Ghatak (2005) for recent surveys of the literature. Also see, for example, Stiglitz (1990); Varian (1990); Banerjee, Besley, and Guinnane (1994); Besley and Coate (1995); Ghatak (1999, 2000); Conning (1999); Armendariz de Aghion (1999); Armendariz de Aghion and Morduch (2000); Armendariz de Aghion and Gollier (2000); Laffont and N'Guessan (2000); Van Tassel (1999); and Tedeschi (2006).

economies, such a legal system is often immature or absent. Therefore, many lenders must rely on some sort of punitive mechanisms, such as the threat of no future credit.

Some studies examining dynamic incentives of default are based on the repeated interaction between a lender and a borrower (see, e.g., Besley, 1995; Morduch, 1999). If a borrower needs continual credit, access to future loans can provide a strong reason to avoid voluntary default on a current loan.[2] Hulme and Mosley (1996) and Armendariz de Aghion and Morduch (2000) using a two-period model, and Tedeschi (2006) and Katchova, Miranda, and Gonzalez-Vega (2006) employing a multiple-period model, examine repayment incentives of strategic default with access to additional credits. Our model is also constructed using repeated interaction in a multiple-period setting to capture dynamic incentives.

The problem of voluntary default is also mitigated by the use of social sanctions, which may include loss of reputation, exclusion from the community, and societal admonishment.[3] Such types of social sanctions are typical for group lending and are also pervasive in individual lending (see, e.g., Churchill, 1999). Besley and Coate (1995) study social sanctions in the context of group lending and others examine this issue within an individual lending setting (Armendariz de Aghion and Morduch, 2000; Tedeschi, 2006).

Our study focuses on how social sanctions are formed in an individual lending credit market when each borrower is small in the sense that the impact of her actions on the default rate in a society is negligible. To the best of our knowledge, none of the past literature examines this crucial feature—namely that social sanctions are determined endogenously in a "large" society. Social sanctions will affect an individual's incentive to default, and the resulting default rate will in turn influence social sanctions.

To examine this issue, we assume the social sanctions each borrower faces have a negative relationship with the default rate in the entire society. Specifically, each borrower does not feel social pressure associated with default when many borrowers default. This type of social sanction could be closely related to the degree of social connectedness in a society. Given the ex ante default rate, the borrower chooses whether or not to default voluntarily. In an equilibrium, the ex post default rate derived from all agents' optimal decisions must be consistent with the ex ante default rate, as in the concept of fulfilled expectation equilibrium.

Nonfinancing threats are effective only when there is a lack of competition or shared access to borrowers' information. Although competition in microfinance markets is attracting interest, actual dealings are often bilateral due to segmentation and exclusivity. Informational, locational, and historical advantages often tend to confer on the lenders the position of a local monopoly. Taking into account that information sharing is now common, and in practice credit bureaus created for microfinance appear in many regions (see, e.g., Campion and Valenzuela, 2001), we consider a situation where there is a single lender or default credit information is shared among multiple lenders, who collectively act as a benevolent institution. Our assumption of a single benevolent lender will provide a good approximation to capture the essence of our problem in the simplest form of the model.

Our analysis suggests that the existence of a credit market highly depends on the lender's financing costs. Financing costs

[2] Continual increases in loan size, known as progressive lending, improve a borrower's incentives to repay over time (see, e.g., Mosley, 1996; Jain and Mansuri, 2003).

[3] In a traditional village, community networks are strong so that everyone knows everyone else. These networks would cause people to act as credible sanctioning devices in situations where a computerized credit agency is missing (see, e.g., Besley and Coate, 1995).

are often influenced by government supports. When financing costs are relatively small, the credit market exists where borrowers have little motivation to default voluntarily, associated with high social sanctions. However, relatively large financing costs cause the credit market to collapse since they reduce social sanctions with intensified motivation for voluntary default.

There has been extensive discussion regarding government intervention and microfinance institutions [see, e.g., Morduch (1999) and Armendariz de Aghion and Ghatak (2005) for a review]. Although there is ongoing debate regarding its effectiveness, our results could justify government supports for microfinancing institutions to improve social welfare through mitigating ex post moral hazard problems.

Our model also aims to present the possibility of two equilibria: a low default rate associated with a low lending rate and high social sanctions in one equilibrium, and a high default rate with a high lending rate and low social sanctions in the other. This multiplicity could provide an explanation for the possibility that social sanctions and the default rate are often different from village to village even though these societies seem to share almost identical environments.

The remainder of the paper is organized as follows. We first present our analytical model of a rural credit market with a single benevolent lender and many borrowers with heterogeneous projects and a dynamic incentive for voluntary default. The next section provides a discussion of results related to the existence of the credit market, the possibility of multiple equilibria, and the role of government support to microfinancing institutions. In the model, social sanctions are endogenized through the default rate in the society. The final section offers several conclusions.

The Model

We consider a simple multiple-period model of a credit market with a single lender (microfinance institution) and many potential borrowers (microentrepreneurs). All agents are risk neutral so that there is no consideration about risk sharing.[4] The lender behaves as a benevolent nonprofit institution, whereby it aims to maximize the expected payoff of the borrowers subject to the zero-profit constraint and the relevant informational constraints, as in Ghatak (1999), Conning (1999), and Tedeschi (2006).

The lender may be thought of as a public lending institution or a non-governmental organization (NGO), which is most often the case for observed microfinancing-lending institutions. The lender is assumed to face a perfectly elastic supply of funds from outside of the society at the risk-free (gross) interest rate $i > 1$. The value of i may be considered as the lender's (gross) financing cost, which is often affected by government supports, such as a subsidy.

Borrowers are endowed with a risky investment project, requiring a fixed investment of a size, normalized at unity, but have no collateral and no funds of their own.[5] At the beginning of each period, the borrower has an opportunity to obtain credit from the lender without operational costs if she has no default history in the past. At the end of the period, the project is successful and generates a gross return $R \in [R_L, R_H]$ with probability $p \in (0, 1)$; otherwise, the project is not successful and generates zero returns.[6]

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[4] In reality, it is likely that lenders are risk neutral, while borrowers are risk averse. However, relaxing this assumption would not significantly change our qualitative results.

[5] It may be considered that credit is simply taken to finance working capital of ongoing production.

[6] We assume p is exogenous so that there is no moral hazard problem with respect to the borrower's effort in undertaking the project, and the only moral hazard problem emerges at the repayment stage.

We assume that R may be different from borrower to borrower and is distributed over $[R_L, R_H]$ according to the uniform distribution function $\Phi(R)$, with $\Phi(R_L) = 0$ and $\Phi(R_H) = 1$.[7] The expected net return of the project is assumed to be positive, i.e., $pR > i$ for all R, whereby all projects should be implemented from the standpoint of social optimality. All agents know the distribution of R that does not change over time, but R is private information and cannot be observed by other agents. The heterogeneity of borrowers comes only from the gross payoff of the project.

The lender cannot identify whether the borrower's default is voluntary or involuntary. Furthermore, the lender does not have enforcement technology, which can be defined as the ability to impose a cost on the borrower in the case of loan default, i.e., the enforcement cost is implicitly prohibitive for the lender. Such an environment is fundamental to our model since this makes it possible for each borrower to strategically default, and consequently a moral hazard problem emerges. If the project fails with zero project return, the borrower will be forced to default involuntarily. In contrast, if the project is successful, she can also default voluntarily without any operational cost in order to obtain the entire generated return R. In this case, the borrower consumes the returns but cannot invest them for future projects.[8]

The lender knows the default history of each borrower. Thus, once she defaults, voluntarily or involuntarily, the borrower can never obtain credit in the future. In addition, borrowers cannot have more than one loan at any period so that borrowing takes place sequentially.

One crucial element of this study is that the borrowers receive a penalty from society in the form of social sanctions when they default either voluntarily or involuntarily. Such penalties take various potential forms, such as material loss and societal admonishment. We do not specify the penalty mechanism, and thus we simply suppose the existence of a social sanction, as in Besley and Coate (1995). Social sanctions are assumed to be dependent on the default rate or the fraction of borrowers who default (q) in the society. Specifically, the payoff loss associated with social sanction is given by a decreasing and convex function $c(q)$, with $c'(q) < 0$, $c''(q) > 0$, and $c(1) \geq 0$. This implies that as more borrowers default, the smaller is the payoff loss associated with social sanctions of default.

To analyze how nonfinancing threats and social sanctions affect the dynamic incentive of borrower default, we consider a society that extends over the following within every period. The benevolent lender offers a loan contract with the (gross) lending rate r to the borrowers who have no default history, and each borrower chooses whether or not to accept the offer. In this study, the term "(gross) lending rate" refers to the (gross) interest rate charged to borrowers. If she accepts the offer, the project is carried out. After success or failure, each borrower chooses whether or not to default voluntarily if the project is successful, while she must default involuntarily if the project fails. If the project is successful and voluntary default is not chosen, the borrower repays r to the lender, and is granted an opportunity to obtain credit in the next period. If the borrower defaults, she can never obtain credit in the future. The same stages are repeated over multiple periods.

Analysis

This section solves the problem of an individual lending credit market and provides several important implications. We first examine the optimal decision of borrowers, taking social sanction c and the

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[7] This assumption is for simplicity. More general formulation might not affect our qualitative results.

[8] For simplicity, this study assumes that savings are not possible. If savings are possible, the punishment associated with nonfinancing threats is likely to be reduced, and hence the likelihood of voluntary default is likely to be increased.

(gross) lending rate r as exogenously given. Then, the lending rate r is endogenously determined under the lender's sustainability constraint, taking social sanction c and the financing cost i as exogenously given. Finally, we find a social equilibrium through endogenizing social sanction under the condition that the ex ante default rate is consistent with the ex post default rate derived from the borrowers' optimal decision and the lender's constraint. Focusing on the impact of a change in the financing cost i for the lender, we also discuss the role of government support to the lender and illustrate how such an intervention affects the rural credit market.

Borrowers' Optimal Decision

This subsection examines the optimal behavior of borrowers with heterogeneous gross project return R, taking the lending rate r and social sanction $c \equiv c(q)$ as exogenously given. Under the participation condition, each borrower with the gross project return R decides whether or not to default voluntarily if the project ends up being successful. Notice that this study assumes a mass of borrowers is employed to conceptualize the large society where an individual borrower is too small to influence the default rate and its corresponding social sanction—i.e., c is completely external to all borrowers when an individual borrower makes a decision.

Let $V \equiv V(r, c, R)$ denote the present value of the expected surplus of the borrower who is faced with the lending rate r, social sanction c, and the project return R when she has no default history. With probability p, the project returns R, and then the borrower chooses whether or not to default voluntarily. If the borrower does not default voluntarily, she then repays r and is in the same situation as before.

On the other hand, if the borrower defaults voluntarily, then she obtains the entire return R minus social sanction c, but now has no opportunity left for borrowing in the future. Moreover, with probability $1 - p$, the project returns zero, the borrower is forced to default with social sanction c, and she has no opportunity left for future credit. When there is no opportunity to borrow, the surplus is assumed to be zero.

Formally, each borrower solves the following recursive equation:

$$(1)\quad V(r, c, R) = \rho\left[p \max_{\{ND, VD\}} \left\{R - r + V(r, c, R), R - c\right\} - (1-p)c\right],$$

under the condition that the participation constraint of the borrower is satisfied such that $V \geq 0$, where ND and VD represent "no voluntary default" and "voluntary default," respectively. The parameter $\rho \in (0, 1)$ denotes the risk-free discount factor for borrowers. Voluntary default has its benefit and cost. The benefit comes from the fact that borrowers never repay r, while the cost is from social sanction and inaccessibility to future credit.

In principle, we determine the borrowers' optimal choice of whether or not to default voluntarily by solving for $V(r, c, R)$. The recursive equation (1) implies that for each borrower with the project return R, there exists a critical value, $\bar{r}(c, R) = (1 - \rho)c + \rho pR$, such that ND is optimal if $r < \bar{r}(c, R)$, and VD is optimal if $r > \bar{r}(c, R)$ and the value of the borrower is given by:

$$(2)\quad V(r, c, R) = \begin{cases} \dfrac{\rho\{p(R-r) - (1-p)c\}}{1 - \rho p} & \text{if } r < \bar{r}(c, R), \\ \rho(pR - c) & \text{if } r > \bar{r}(c, R). \end{cases}$$

This equation simply requires borrowers to choose not to default voluntarily if the lending rate is relatively low, while they should choose to default voluntarily if the lending rate is relatively high.

In Figure 1, the value when the borrower with project return R and social sanction c

chooses to default voluntarily is shown by line BC, while the value when she chooses not to default voluntarily is shown by line DE. Notice that the value of $\rho(pR - c)$ could be interpreted as the reservation payoff of voluntary default for the borrower with R and c.

In our model, such a reservation payoff can be supported through two sources of information asymmetry: borrowers' action of whether or not to involve strategic default, and their information of the level of the gross project return. Since $\bar{r}_c(c, R) = 1 - \rho > 0$ and $\bar{r}_R(c, R) = \rho p > 0$, a rise in c and R raises the critical value $\bar{r}(c, R)$ that differentiates the optimal decision.

We now attempt to derive the default rate, which is represented by the fraction of borrowers who default voluntarily or involuntarily, based on the optimal decision for the individual borrower. Using equation (2) with $\bar{r}(c, R) = (1 - \rho)c + \rho pR$, we determine the borrower chooses to default voluntarily if her project return is small enough that $R < \overline{R}(r, c)$. Conversely, she chooses not to default voluntarily if it is large enough that $R > \overline{R}(r, c)$ where $\overline{R}(r, c) = \{r - (1 - \rho)c\}/(\rho p)$. Since R is distributed over $[R_L, R_H]$ according to the uniform distribution function $\Phi(R)$, the default rate in the society with the lending rate r and social sanction c is described by:

$$(3)\quad q(r, c) = \begin{cases} 1 - p & \text{if } r < \bar{r}(c, R_L), \\ 1 - p[1 - \Phi(\overline{R}(r, c))] & \text{if } r \in (\bar{r}(c, R_L), \\ & \qquad \bar{r}(c, R_H)), \\ 1 & \text{if } r > \bar{r}(c, R_H). \end{cases}$$

Notice that for any $r \in (\bar{r}(c, R_L), \bar{r}(c, R_H))$, the default rate $q(r, c)$ is increasing in the lending rate r but is decreasing in social sanction c, since

$$q_r(r, c) = \frac{1}{\rho(R_H - R_L)} > 0$$

and

$$q_c(r, c) = -\frac{1 - \rho}{\rho(R_H - R_L)} < 0.$$

Figure 2 describes the graph of equation (3), representing the relation between the lending rate r and the default rate q. An increase in c causes the graph to shift parallel to the right. In terms of the fraction of the borrowers who default voluntarily, $q(r, c) - (1 - p)$, no borrowers default voluntarily if the lending rate is low enough such that $r < \bar{r}(c, R_L)$, all borrowers default voluntarily if the lending rate is high enough such that $r > \bar{r}(c, R_H)$, and only borrowers with a relatively small project return R default voluntarily if the lending rate is in the intermediate range such that $r \in (\bar{r}(c, R_L), \bar{r}(c, R_H))$.

Equilibrium Under Exogenous Social Sanction

This subsection examines the equilibrium outcome under the benevolent lender with social sanction c and the financing cost i as given. The lender faces the default rate described in equation (3) and decides the lending rate whereby the following zero-profit condition holds:

$$(4)\quad (1 - q)r = i,$$

or $q = 1 - i/r$. Equations (3) and (4) are the two conditions which simultaneously determine the lending rate, $r^* \equiv r^*(c, i)$, and the default rate, $q^* \equiv q^*(c, i)$. Letting $c_1 \equiv c_1(i)$ and $c_2 \equiv c_2(i)$ such that

$$c_1(i) = \frac{1}{1 - \rho}\left(2\left[i\rho(R_H - R_L)\right]^{1/2} - \rho p R_H\right)$$

and

$$c_2(i) = \frac{1}{1 - \rho}\left(\frac{i}{p} - \rho p R_L\right),$$

with $c_1 \leq c_2$, we first obtain the following result related to the existence of a credit market.

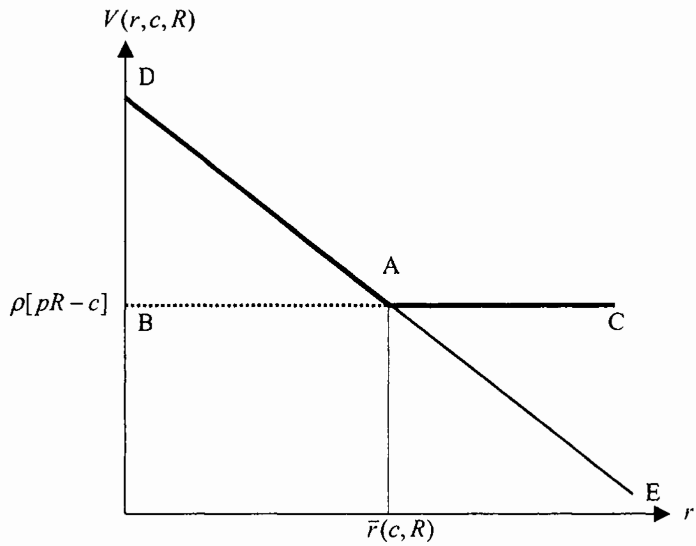

Figure 1. Strategic Default

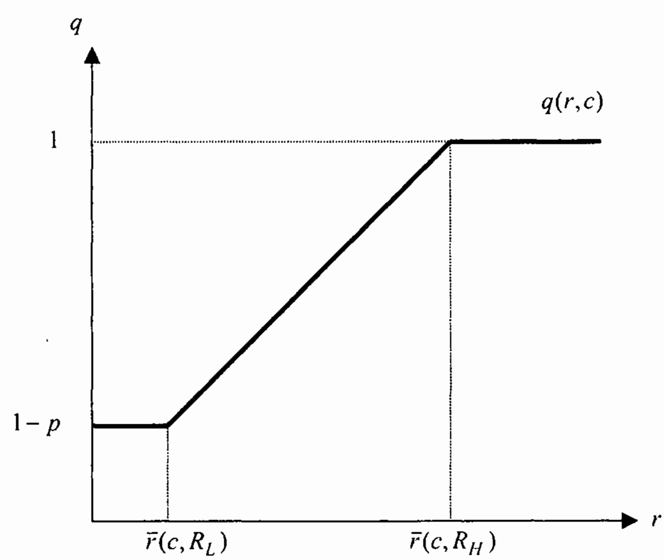

Figure 2. Gross Lending Rate and Default Rate

LEMMA 1: Equilibrium Under Exogenous Social Sanction

Suppose the financing cost i is not very large such that $i < \rho p^2(R_H - R_L)$. Then:

- If $c < c_1(i)$, no credit market exists.
- If $c \in (c_1(i), c_2(i))$, there exists a credit market with the lending rate

  $$r^*(c, i) = \frac{\bar{r}(c, R_H) - \{[\bar{r}(c, R_H)]^2 - 4i\rho(R_H - R_L)\}^{1/2}}{2}$$

  and the default rate

  $$q^*(c, i) = 1 - \frac{i}{r^*(c, i)} \in (1 - p, 1),$$

  where the borrowers with a relatively low project return such that $R < \overline{R}(r^*(c, i), c)$ default voluntarily, while those with a relatively high project return such that $R > \overline{R}(r^*(c, i), c)$ do not.
- If $c > c_2(i)$, there exists a credit market with the lending rate $r^* = i/p$ and the default rate $q^* = 1 - p$.

  (See the Appendix for the proof of Lemma 1.)

This result implies that whether or not a credit market exists depends largely on the payoff loss from social sanctions; i.e., if a social sanction is small enough, then a credit market cannot exist. In Figure 3, curve BC represents the lender's constraint (4), while other kinked graphs represent the borrowers' condition (3). The graphs of the lender's constraint and the borrowers' condition are tangent to each other for some level of social sanction under the assumption of $i < \rho p^2(R_H - R_L)$.[9]

[9] If the financing cost is relatively large such that $i > \rho p^2(R_H - R_L)$, then there cannot exist an interior equilibrium in the sense that the default rate is above $1 - p$. In this case, no credit market exists if $c < c_2$: and there exists a credit market with the gross lending rate $r^* = i/p$ and the default rate $q^* = 1 - p$ if $c > c_2$.

Recall that an increase in social sanction c decreases $q(r, c)$, which causes the kinked line to shift to the right in Figure 3. Solid, dotted, and dashed graphs (kinked lines) represent the graphs of the borrowers' condition corresponding to relatively small, intermediate, and relatively large values of social sanction, respectively. Notice that the dotted line is tangent to the lender's constraint at point A, which means it corresponds to the critical value $c_1(i)$. If $c < c_1(i)$, there are no intersections of the two graphs. In this case, the pool of borrowers seeking credit never gives the lender's required return at any gross lending rate r due to an intensified motivation toward strategic default. This is parallel to a "collapsed" credit market in Mankiw (1986).

In contrast, if $c > c_1(i)$, all potential borrowers obtain credit at some level of the lending rate in a credit market. In this situation, the two graphs that represent the conditions could intersect more than once. However, we believe it may be reasonable to restrict ourselves to the intersection at which the slope of $q = 1 - i/r$ is larger than that of $q = q(r, c)$, or the intersection associated with a lower default rate.[10]

[10] The equilibrium associated with a lower default rate is stable, while the other equilibrium is unstable. To check this, we suppose that the lending rate, r^c, is larger than the equilibrium level, r^e, associated with a lower default rate. In this case, the default rate derived from the borrowers' condition $q = q(r^c, c)$ is smaller than the zero-profit level of the default rate $q = 1 - i/r^c$. This in turn allows the benevolent lender to revise the lending rate downward. On the other hand, we suppose that the lending rate, r^c, is smaller than the equilibrium level, r^e, associated with a lower default rate. In this case, the default rate derived from the borrowers' condition $q = q(r^c, c)$ is larger than the zero-profit level of the default rate $q = 1 - i/r^c$. This in turn causes the benevolent lender to revise the lending rate upward. Thus, the equilibrium associated with a lower default rate is stable when the slope of $q = 1 - i/r$ is larger than that of $q = q(r, c)$. Another possible reason may be that the single lender is benevolent in the sense that she prefers a lower default rate in the society with the zero-profit condition. The social optimality requires the implementation of all projects due to the assumption of $pR > i$ for all R. In the dynamic sense, a lower default rate implies a higher social welfare since borrowers who defaulted in the past lose any access to future credit and any opportunity to finance future projects.

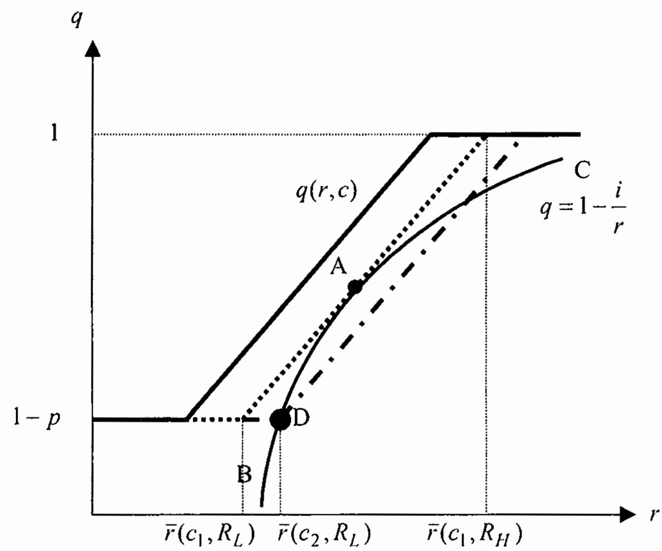

Figure 3. Credit Market Under Exogenous Social Sanction: Impact of Change in Social Sanction

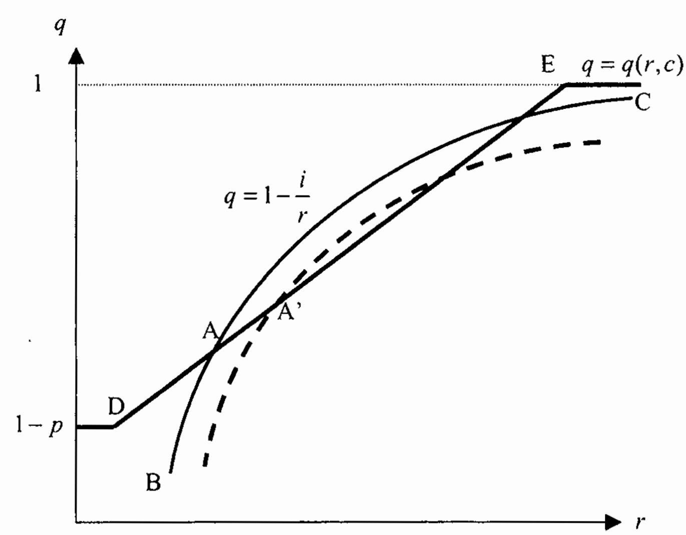

Figure 4. Credit Market Under Exogenous Social Sanction: Impact of Change in Financing Cost

Notice at $c = c_2(i)$, the graphs of the two conditions intersect at point D. This implies that if $c > c_2(i)$, the equilibrium point binds the minimum attainable level of the default rate $1 - p$, and point D always represents the unique equilibrium, where the lending rate and the default rate are represented by $r^*(c, i) = i/p$ and $q^*(c, i) = 1 - p$, respectively.

In particular, if $c \in (c_1(i), c_2(i))$, the equilibrium is shown by some point between point A and point D on curve BC in Figure 3. Some borrowers with a relatively small project return default voluntarily. The lending rate $r^*(c, i)$ and the default rate $q^*(c, i)$ are decreasing in social sanction c since

$$r_c^* = \frac{1-p}{2} \times \left\{ 1 - \frac{2\bar{r}(c, R_H)}{\left\{\left[\bar{r}(c, R_H)\right]^2 - 4ip(R_H - R_L)\right\}^{1/2}} \right\} < 0$$

and

$$q_c^* = \frac{i}{\left[r^*(c, i)\right]^2} r_c^*(c, i) < 0.$$

Graphically, a rise in social sanction c causes the graph of $q = q(r, c)$ to move to the right, and thus the equilibrium point to move toward point D in the direction of the southwest side along curve BC. A rise in social sanction discourages borrowers from defaulting voluntarily, which in turn makes it possible for the benevolent lender to reduce the lending rate. In summary, as the degree of social sanction intensifies, the society moves from the nonexistence of a credit market, to the existence of a market with some voluntary default, to the existence of a credit market without voluntary default.

Notice also that if $c \in (c_1(i), c_2(i))$, then $r^*(c, i)$ and $q^*(c, i)$ are increasing in the financing cost i since

$$r_i^* = \frac{p(R_H - R_L)}{\left\{\left[\bar{r}(c, R_H)\right]^2 - 4ip(R_H - R_L)\right\}^{1/2}} > 0$$

and $q_i^* > 0$. Graphically, a rise in the financing cost i causes the graph of $q = 1 - i/r$ in Figure 4 to move downward, and thus the equilibrium point to move from point A to point A′ in the direction of the northeast side along line DE. A rise in the financing cost compels the lender to raise the lending rate, which in turn encourages borrowers to default voluntarily.

Social Equilibrium

In this subsection we consider a situation where social sanction c is determined endogenously. Letting $s \in [1 - p, 1]$ denote the ex ante default rate in the society, we represent the ex ante social sanction by $c = c(s)$, which is decreasing and convex in s. This specification requires that each borrower feels more social pressure from default as fewer borrowers default. The default rate discussed in the previous section may be called the ex post default rate derived from the borrowers' optimal decision and the lender's constraint associated with the ex ante social sanction c and the financing cost i.

Let $s_1 \equiv s_1(i)$ and $s_2 \equiv s_2(i)$ such that $c_1 = c(s_1) < c(s_2) = c_2$, i.e., $s_1 = c^{-1}(c_1) > c^{-1}(c_2) = s_2$ due to the assumption that $c(s)$ is monotone decreasing in s. By Lemma 1, if $s > s_1(i)$, no credit market exists. If $s \in (s_2(i), s_1(i))$, all borrowers obtain credit in a credit market, but some borrowers with a relatively low project return default voluntarily. If $s < s_2(i)$, all borrowers obtain credit in a credit market without any incentive for voluntary default. Then, given the ex ante default rate $s < s_1(i)$ and the financing cost i, a credit market exists, and the ex post default rate is described by:

$$\hat{q}(s, i) = \begin{cases} 1 - p & \text{if } s < s_2(i), \\ q^*(c(s), i) & \text{if } s \in (s_2(i), s_1(i)). \end{cases}$$

For any $s \in (s_2(i), s_1(i))$, the derivative of $\hat{q}(s, i)$ with respect to s is given by $\hat{q}_s(s, i) = q_c^*(c(s), i)c'(s)$. Since $c'(s) < 0$ and $q_c^*(c(s), i) < 0$, $\hat{q}(s, i)$ is increasing in s over $(s_2(i), s_1(i))$.

We now introduce the concept of a social equilibrium (a fulfilled expectations equilibrium) in the society, where all borrowers correctly foresee the default rate. In a social equilibrium, the borrowers' conjectured default rate prior to their decision must be equal to the resulting default rate. Thus, the condition for a social equilibrium is that the ex ante default rate s must be consistent with the ex post default rate $\hat{q}(s, i)$, which is derived from the lender's zero-profit condition and the borrowers' decision problem based on the ex ante or conjectural default rate in the society:

$$\hat{q}(s, i) = s.$$

This condition implies the following result:

- PROPOSITION 1. *Suppose that $\hat{q}_s < 1$ for all $s \in (s_2(i), s_1(i))$, with $\hat{q}(s_1(i), i) < s_1(i)$. Then there exists a unique (stable) social equilibrium, where the default rate is $\hat{s} \equiv \hat{s}(i) \in [1 - p, 1)$.*

The value of $\hat{q}_s = q_c^*(c(s), i)c'(s)$ measures the effect of a rise in the ex ante default rate s on the ex post default rate $\hat{q}(s, i)$ if $s \in (s_2(i), s_1(i))$. The condition of $\hat{q}(s_1(i), i) < s_1(i)$ guarantees the existence of a social equilibrium. Also, the condition of $\hat{q}_s = q_c^*(c(s), i)c'(s) < 1$ is necessary for the uniqueness of a social equilibrium, requiring that the sensitivity of the ex post default rate in response to a change in social sanctions is relatively small, and the sensitivity of social sanctions in response to a change in the ex ante default rate is relatively small.[11]

Figure 5 (panels A, B, and C) illustrates the graph of $\hat{q}(s, i)$, where the slope of the graph is assumed to be less than unity. The social equilibrium is represented by the intersection of the graph of $\hat{q}(s, i)$ and the 45-degree line. In general, the shape of the graph of $\hat{q}(s, i)$ depends on $q^*(c, i)$, $c(s)$, $s_1(i)$, and $s_2(i)$. Figure 5A shows that the society has no credit market, and Figures 5B and 5C show that the credit market exists with some level of the equilibrium default rate $\hat{s} \equiv \hat{s}(i) \in [1 - p, 1)$. Figure 5B illustrates the situation where some borrowers with a relatively low project return default voluntarily. The situation where no borrowers default voluntarily is illustrated by Figure 5C.

To obtain implications from Figure 5, we closely examine the role of the financing cost to the lender, i, which is often affected by government support. Notice that $s_1(i)$ and $s_2(i)$ are decreasing in i since $c_1(i)$ and $c_2(i)$ are increasing in i. Notice also that $\hat{q}_i(s, i) > 0$ since $q_i^*(c(s), i) > 0$. These properties imply that the graph of $\hat{q}(s, i)$ over the domain $(s_2(i), s_1(i))$ is likely to shift to the left as the financing cost i rises.

Thus, Figure 5A corresponds to the case where the financing cost is relatively large such that no credit market exists. In contrast, Figure 5C corresponds to the case where the financing cost is relatively small such that a credit market exists and borrowers never default voluntarily. Furthermore, Figure 5B suggests that for an intermediate range of the financing cost, a credit market exists with some voluntary defaults in a social equilibrium, i.e., the equilibrium default rate is interior at $\hat{s}(i) \in (1 - p, 1)$. In this case, a change in the financing cost positively affects the equilibrium default rate since $\hat{s}'(i) = q_i^*/(1 - q_c^*c'(s)) > 0$ due to $q_i^* > 0$ and $1 > \hat{q}_s = q_c^*c'(s)$.

The intuition behind these results is as follows. If the financing cost is relatively large, the lender requires a higher lending rate to meet her constraint, given an ex ante default rate and an ex ante social sanction.

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[11] To check the stability of a social equilibrium, we suppose that the conjecture of the default rate, s^c, is larger than the equilibrium level, $\hat{s}$. In this case, the conjecture of the default rate is larger than the ex post default rate that is based on this conjecture, i.e., $s^c > \hat{q}(s^c, i)$. This in turn causes agents to revise their conjecture downward. On the other hand, we suppose that the conjecture of the default rate, s^c, is smaller than the equilibrium level, $\hat{s}$. In this case, the conjecture of the default rate is smaller than the ex post default rate, i.e., $s^c < \hat{q}(s^c, i)$. This in turn causes agents to revise their conjecture upward. Thus, the social equilibrium is stable under the condition $\hat{q}_s < 1$.

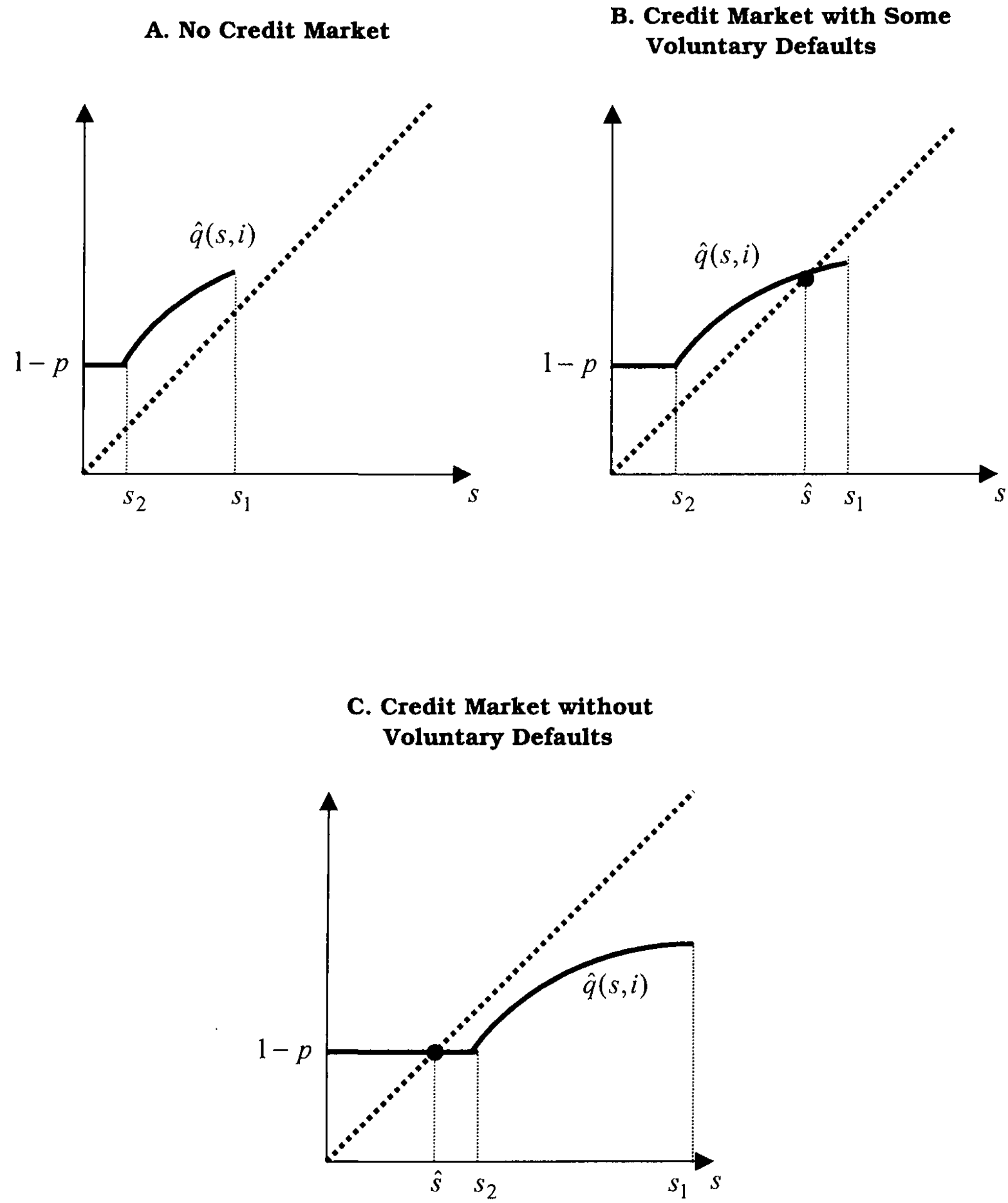

Figure 5. Social Equilibrium

This would, in turn, exacerbate moral hazard and cause more borrowers to default voluntarily. Voluntary default would then raise the default rate and hence reduce social sanctions. The rising default rate forces the lender to increase the lending rate further, and the decline in social sanctions causes more borrowers to default voluntarily. This logical sequence repeats, and as a result, the credit market collapses, as shown in Figure 5A.

In contrast, if the financing cost is relatively small, the lender can set the lending rate at a lower level. This would, in turn, cause fewer borrowers to default voluntarily, thereby reducing the default rate and increasing social sanctions. The declining default rate compels the lender to reduce the lending rate further. Also, due to the rise in social sanctions, fewer borrowers default voluntarily. This logical sequence repeats, and as a result, a credit market exists without any voluntary default incentive, as depicted in Figure 5C.

The results reported above yield some important implications for government support provided to a benevolent lender.

- First, government support to reduce the overall financing cost could be an effective means to allow for a credit market to exist. When the financing cost is high in a society, a credit market may not be supported in a social equilibrium, which induces a serious social inefficiency (Figure 5A).

- Second, government support could also be effective in reducing the default rate even when a credit market exists. If there exist borrowers who have an incentive to default voluntarily, government support to reduce the financing cost could be helpful to weaken the default incentive.

- Third, from the standpoint of social efficiency, the existence of a credit market improves social welfare by giving potential borrowers access to financing and the ability to implement their profitable projects. The reduction in the default rate could also allow more borrowers to obtain future credit to finance their projects, resulting in improved social welfare. One crucial driving force is that financing costs affect social sanctions of default which are dependent on the default rate in the society.

These results provide a justification for the positive side of subsidies and are partly consistent with the reality that much of the microfinancing movement takes advantage of various subsidies from governments, donors, and charities, although there remains ongoing debate about the effectiveness of such subsidies (see, e.g., Armendariz de Aghion and Ghatak, 2005).

More interestingly, the society illustrated in Figure 6 has two (stable) social equilibria, A and B (point C represents an unstable social equilibrium). In this case, the condition of $\hat{q}_s = q_c^*(c(s), i)c'(s) < 1$ in Proposition 1 is violated for some $s \in (s_2(i), s_1(i))$; i.e., the sensitivity of the ex post default rate in response to a change in social sanction is relatively large, or the sensitivity of social sanction in response to a change in the ex ante default rate is relatively large. The equilibrium default rate is larger than $1 - p$ at point B and is equal to $1 - p$ at point A. Each of the social equilibria attains different levels of the default rate, the lending rate, and social sanctions.

This result has an important implication regarding the relationship among the default rate, the lending rate, and social sanctions. In one social equilibrium, the higher default rate is invariably associated with the higher lending rate and the less intense social sanctions. In the other social equilibrium, the lower default rate is invariably associated with the lower lending rate and the more intense social sanctions. In the former social equilibrium, many borrowers choose voluntary default because others do. Conversely, in the latter, no borrowers elect voluntary default because others do not.

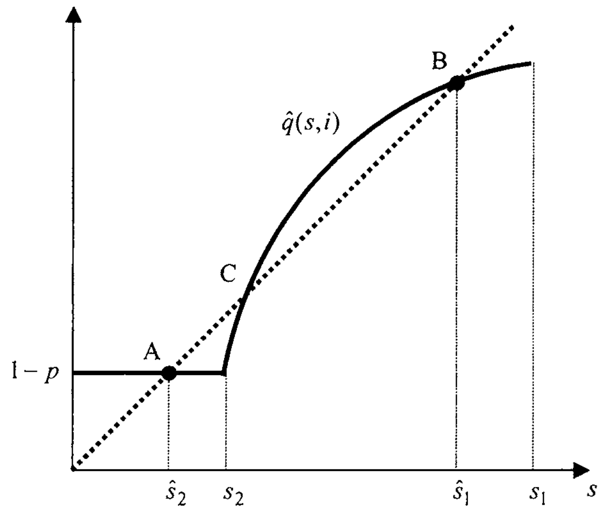

Figure 6. Multiple Social Equilibria

Such multiplicity induces the indeterminacy of the resulting outcome, which would be consistent with observations that collective action sometimes succeeds and sometimes fails. This could provide an explanation for the possibility that the default rate is different from village to village even though these societies seem to share an almost identical environment.

Conclusion

Policy makers in many developing countries have attempted to mitigate poverty issues through improving rural financial markets, and the microfinancing movement has emerged as a promising way to reconsider credit accessibility for the poor. The ability to secure high repayment rates is a crucial determinant of the sustainability of microfinancing institutions.

To examine the dynamic incentive of default in individual lending markets, this study has focused upon two important mechanisms: the nonfinancing threat and social sanctions, through constructing the dynamic repeated model with a single benevolent lender and potential borrowers with heterogeneous projects. In particular, utilizing the concept of a fulfilled expectations equilibrium, the model endogenously determines social sanctions through social interactions among borrowers in a "large" society, where each borrower is too small to influence the default rate in the entire society.

We have examined the role of the financing cost for the lender on the relationship among the borrower default rate, the lending rate, and social sanctions, since the financing cost is often affected by government support. The main results indicate that a credit market exists with a relatively small financing cost, while a relatively large financing cost causes the credit market to collapse even though projects may be profitable in terms of social optimality. These results provide a justification for government support of microfinancing institutions, which has been widely observed as subsidization (see, e.g., Armendariz de Aghion and Ghatak, 2005).

Another important result is that the model presents the possibility of multiple social equilibria in which: (*a*) there is a low default rate associated with intense social sanctions in one equilibrium, and (*b*) a high default rate with less intense social sanctions in the other. This finding could provide one possible explanation for the significant differences in the default rate and the interest rate charged to borrowers from village to village, as may be shown anecdotally. The formation of social sanction in a village plays an important role in deriving this multiplicity through collective action.

Our aim has been to illustrate important, plausible features of nonfinancing threats and social sanctions, which are the effective devices for mitigating the dynamic incentive of default in individual lending markets. A necessary step in a future research study should be to validate empirically this model by collecting actual data in developing economies. There remain many unsettled questions in rural credit markets. Our hope is that this model provides insights which can be applied further to help reduce poverty in developing economies.

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Appendix: Proof of Lemma 1

We first derive $c_1(i)$ and $c_2(i)$. Since the graph of $q = q(r, c_1(i))$ is tangent to that of $q = 1 - i/r$ at point A in text Figure 3, and since the graph of $q = q(r, c_2(i))$ and that of $q = 1 - i/r$ intersect at point D, $(\bar{r}(c_2(i), R_L), 1 - p)$, we obtain:

$$c_1(i) = \frac{2\left[i\rho(R_H - R_L)\right]^{1/2} - \rho p R_H}{1-\rho}$$

and

$$c_2(i) = \frac{1}{1-\rho}\left(\frac{i}{p} - \rho p R_L\right).$$

Notice that the condition of $i < \rho p^2(R_H - R_L)$ requires that the slope of $q = 1 - i/r$ is steeper than that of $q = q(r, c_2(i))$ at the neighborhood of $r = \bar{r}(c_2(i), R_L)$, with $r > \bar{r}(c_2(i), R_L)$; i.e., point A is located at the northeast side of point D in Figure 3.

Since $q_c(r, c) < 0$ for all $r \in (\bar{r}(c, R_L), \bar{r}(c, R_H))$, a rise in c causes the graph of $q = q(r, c)$ to shift to the right. Thus, it is directly observed that there are three cases depending on c. First, if $c < c_1(i)$, then there is no intersection of $q = q(r, c)$ and $q = 1 - i/r$, which implies that no credit market exists. Second, if $c > c_2(i)$, then there are two intersections, one of which is point D. Since we restrict ourselves to the intersection associated with a lower default rate, point D is attained in the society, which implies that there exists a credit market with the lending rate $r^* = i/p$ and the default rate $q^* = 1 - p$. Third, if $c \in (c_1(i), c_2(i))$, then there are two intersections, one of which is between point A and point D on curve BC, say point E. Similarly, since we restrict ourselves to the intersection associated with a lower default rate, point E is attained in the society, which implies that there exists a credit market with the lending rate $r^*(c, i)$ and the default rate $q^*(c, i) = 1 - i/r^*(c, i) \in (1 - p, 1)$,

$$r^*(c, i) = \frac{\bar{r}(c, R_H) - \left\{[\bar{r}(c, R_H)]^2 - 4i\rho(R_H - R_L)\right\}^{1/2}}{2}.$$

In this case, the optimal decision rule discussed in the "Borrowers' Optimal Decision" subsection implies that borrowers with a relatively low project return such that $R < \overline{R}(r^*(c, i), c)$ choose voluntary default, while those with a relatively high project return such that $R > \overline{R}(r^*(c, i), c)$ do not. □

Economic Value of Tradable Farmland Use Rights and Mortgage Loans in China

H. Holly Wang

Abstract

This paper first discusses the possibility of market-transferable land use rights and mortgage loans in China, and then shows farmers' welfare gain in the presence of such mortgage loans with a theoretical model. Cases of risks and asymmetric information are studied, and policy implications are drawn.

Key words: asymmetric information, land use rights, mortgage loan, risk, welfare

Three decades ago, China abandoned its collective farming system and adopted the Household Responsibility System (HRS) in its agriculture sector. Under HRS, farmers obtained farmland use rights through contracting with their villages, which are the legal owners of the land. Granting land use rights to farmers was a radical change from the previous collective system, and thus had a great impact on agricultural production and rural income (Lin, 1992; McMillan, Whalley, and Zhu, 1989; Rozelle and Swinnen, 2004). HRS helped lift hundreds of millions of rural households out of poverty (World Bank, 2001).

Despite apparent overwhelming benefits, the key component of HRS—namely the de-collectivization of farmland—is still not fully compatible with the market economy. Land ownership remains in villages, and administrative adjustment and redistribution of land based on demographic changes have continued to prevail (Benjamin and Brandt, 2002). Complaints of unfair farmland transfers to urban development, determined by local governments, have also been voiced.

This land tenure insecurity causes disincentives in long-term investment (Li, Rozelle, and Brandt, 1998; Jacoby, Li, and Rozelle, 2002) and has contributed to the recent stagnation in agricultural productivity growth. The prohibition of land transfers also leads to land fragmentation and diseconomies of size, thereby impeding agricultural efficiency (Chen and Brown, 2001).

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To give farmers more assurance concerning land use rights, the Chinese government has issued policies and regulations since the late 1990s to promise the contracting system for at least 50 years. The Property Law of the People's Republic of China (China Congress, 2007), passed in early 2007, further clarifies the regulations on farmland use rights, referred to as "land contracting rights." The Law separates the ownership and use rights of land, and also requires local governments to issue certificates for the land use rights to contracting farmers. It allows the rights to be transferred through subcontracting, mutual exchange, and bequest, but not to be traded or used as loan collateral. Because the market-based transferability has positive efficiency implications (Carter, 2000), the prohibition of the trade would cause inefficiency in agricultural production.

Liberalizing the market for land, or at least land use rights, is viewed as a crucial step in the transition from a centrally controlled economy to a market economy (Ravallion and van de Walle, 2006a). The market-based transferability of land, the most important input in agricultural production, also has significant efficiency implications from a production point of view (Carter and Yao, 2002).

Furthermore, without the market value of the land or land use rights being counted as equity, farmers in China appear quite poor and have no collateral when they seek credits. The tradable certificates of the land use rights, if not land, will also have financial value in terms of helping farmers obtain credits. Credits allow better productive choices, leading to higher profits (Blancard et al., 2006).

Because legal sources of rural finance are rather limited, a number of informal financing activities have been observed in rural China in the past few years. Some of the financial activities involve mortgaging of homes or machinery. However, because these activities are not approved by the government, without professional regulations or legal support, the transactions are often problematic (Cao, 2006). The lack of commercial rural finance is by and large due to high risks in rural investment and a lack of collateral. Issues related to land ownership transfers and mortgage loan[1] contracts have been investigated (Legut, Potters, and Tijs, 1994; Bell and Clemenz, 2006).

A review of the current literature reveals no studies on the welfare implications under uncertainty and asymmetric information for land mortgage loans, especially with application to Chinese agriculture. Accordingly, this study explores the possibilities for market-tradable land use rights and mortgage loans in China, with the objective of showing the economic value of such mortgage loans through farmers' welfare gain.

The remainder of the paper is organized as follows. The possibility of tradability of land use rights and mortgage loans is first discussed, using examples from other countries. The model structure of cases in the presence and absence of mortgage loans is then presented, in combination with an examination of the welfare implications. The next two sections highlight cases where farmers are not homogeneous in risks and can strategically default the mortgage loan, as well as the case when the creditor has a desire for the land and induces foreclosure, respectively. These discussions bring attention to potential problems that the mortgage loan market may experience in practice. The final section provides concluding remarks and addresses policy implications for China.

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[1] In this paper, the land mortgage loan refers to the loan using land as collateral. The loan is not used to purchase the land, but can be used for any other business purposes. It is a type of equity loan.

Market-Based Transfers of Land Use Rights and Mortgage Loans

Land ownership has been a very sensitive issue in China. The fear of vast land loss from rural households has prevented the government from fully privatizing farmland. The separation of the ownership and use rights gives partial property rights to farmers, which is a revolutionary step leading to a market-based land transfer system.

The market-based transfer of land use rights can be the next step in moving toward a complete land market and consequently improving economic efficiency. In China, the Property Law authorizes a 30-year use rights certificate to each current contractor with the possibility of renewal. The tradable certificate should be considered divisible across any time frame within the 30 years for agricultural use. This will improve the efficiency of land use, and also protect the current land contractors from permanently losing their use rights. The trading value of the certificate represents the present value of the land rents during the time frame. Once the use rights are made tradable, mortgage loans with the land use rights certificates as collateral will be possible. Such policies have been practiced in several other countries.

Like China, Vietnam abandoned its collective farming system and contracted the land use rights to farmers in 1988 for 15 years while keeping the ownership with the State. The land use rights were not tradable at this stage. Passed in 1993, the new land law allows an increased contract term and the heritage, transfer, exchange, lease, and mortgage of land use rights, which include almost the entire property rights. The land use rights are warranted by a tradable certificate. The tradable and inheritable certificate is expected to increase land consolidation to improve efficiency and to provide land security, thus encouraging long-term investment as well as improving welfare through access to credit, using mortgage loans (Do and Iyer, 2003). Hare (2008) showed empirically that the possession of tradable certificates correlates with increased long-term investment in Vietnam.

In their recent study of land reform in Vietnam, March and MacAulay (2006) provide evidence that in the late 1990s and early 2000s, land use rights were traded, land consolidation appeared, investment in irrigation increased, changes in crops occurred, commercial agriculture started, and a small percentage of landless rural families also emerged. The rural poverty rate during that period was actually reduced. Ravallion and van de Walle (2006b) report that the sales of the land use rights in Vietnam were more associated with attractive off-farm opportunities and that the portion of landless rural people is smaller among the poor.

In an economy with imperfect credit markets, the trade of a portion of the property rights is an alternative way to transform illiquid assets into cash. Another example is land-pawning contracts in rice-growing areas in the late 1980s in the Philippines. In a land-pawning transaction, the pawner temporarily transfers his/her cultivation rights to the pawnee in return for a loan, and can redeem the rights upon loan repayment. A permanent transfer of cultivation rights may result if a severe default occurs (Nagarajan, David, and Meyer, 1992). The land-pawning situation existed for three reasons: (*a*) land ownership was not allowed to be transferred during that period (Nagarajan, Quisumbing, and Otsuka, 1991), (*b*) technological innovations in rice farming have increased the value of cultivation, and (*c*) formal credit markets were not well developed.

It is common to observe an increase in the liquidities of land through the device of a pledge. One of the most important features of the land market in Wales in the 14th and 15th centuries was the widespread use of the gage, or pledge

(Smith, 1976). A pledge has always been a convenient and attractive way of securing credit for borrowers and lenders of funds in financial markets.

The equity concern is always present whenever any land-privatizing policy is considered. Just like 30 years ago when China first adopted HRS, there was a concern that households with fewer laborers and lower farming skills might not be able to produce enough food for themselves. However, the benefit of gained efficiency dominates the cost of increased inequality by a large margin. China has created a huge number of nonfarm employment opportunities over the past three decades that can absorb landless rural laborers. A social welfare system is also being constructed. These two factors can support further land reform.

Meanwhile, restrictive policy measures can still be taken to prevent the high concentration of land, such as setting a land size ceiling for each household as the Vietnamese government does. The land use rights tradability can also be piloted first in areas where off-farm employment is more accessible. These policies will make the reform process smoother and less drastic.

The Structure Model for Mortgage Loan Contract

In this section, the economic benefit when mortgage loans are introduced into the rural economy is illustrated with a theoretical model. A simple deterministic case is first introduced and then extended into a stochastic case. Two agents in the economy are considered, farmers and creditors, as well as two assets, land use rights and money. Households have no money but have endowments of long and secured land use rights that are legally transferable. They are also endowed with family resources without any other income-generating opportunity. Creditors have initial endowments of money only. Each farmer holds a plot of contracted land, which is homogeneous in size and indivisible. The creditor has cash and access to a risk-free investment opportunity with a rate of return, r_s.

There are two mutually exclusive technologies in farming, represented as conventional and hi-tech, respectively. Under the conventional technology, the farm household's reservation alternative, the output is produced by the contracted land and family resources jointly. Under the hi-tech alternative, the production requires commercial inputs. The value of these inputs is a choice variable, K.

The Case of Risk-Free Production

The value of output under the conventional technology is q, $q > 0$, in each period, and $f(K)$ under the hi-tech alternative, $f(K) - (1 + r_s)K > q$ when $K > 0$; $f(\cdot)$ is the production function for a particular farmer. The input is assumed to be purchased at the beginning of each period with the loan at the risk-free rate of interest, while revenue is realized at the end of the period. The higher profit from hi-tech for at least some farmers, depending on their farming skills, is necessary because otherwise no one will adopt the technology when the conventional alternative is feasible.

Based on the current policy in China, we study the production model within a fixed number of years, n. For multi-period production activities, the present values of the profits these farmers make are, respectively:

$$(1)\quad W^c = \frac{q\left(1-(1+r)^{-n}\right)}{r}$$

and

$$(2)\quad W^h = \frac{\left[f(K)-(1+r_s)K\right]\left(1-(1+r)^{-n}\right)}{r}$$

at the optimum level of K. Here W^i indicates the farmer's welfare under technology i, and r is the farmer's opportunity cost of capital. There is no growth in the sense that the revenue and cost remain the same in each period. The long-run profit gain of adopting the hi-tech production is the difference:

$$(3)\quad W^h - W^c = \frac{\left[f(K) - (1 + r_s)K - q\right]\left(1 - (1 + r)^{-n}\right)}{r}.$$

However, because farmers have no cash endowment to purchase the commercial input K, a loan of that size is necessary for them to achieve the higher profit. More likely, a hi-tech production requires up-front investments such as greenhouses, patents, irrigation, etc.; thus, a loan of a larger size is necessary. Without enough equity as collateral, it is very difficult for farmers to obtain such commercial loans because the creditors recognize the possibility of default, even though the production is assumed risk-free.

As a common practice in finance, collateral is required, and the only sizable equity farmers have for use as collateral is the land or the long-term land use rights certificate. Consequently, the opportunity cost of the lack of market-transferable land use rights is equal to the opportunity cost of the lack of credit, which is just the opposite of the long-run profit gain from adopting the hi-tech production as calculated in (3). The aggregated farmer welfare gain is the sum of such calculated gains across all farmers whose values are positive. Those who do not have a positive value will remain with the conventional technology.

In the following subsection, we introduce risks into the production systems.

Case with Production Uncertainty

When risk is present, we assume there are two states of nature causing production to succeed or fail. There exist exogenous probabilities of production failure for both technologies, p^i. The one for the hi-tech technology where $i = h$ is higher than for the conventional technology where $i = c$, $p^h > p^c$. In the event of a production failure, the output has zero cash value in both cases. Now $f(K)$ is assumed to be increasing, strictly concave, and twice differentiable, and depends on the production efficiency of individual producers. All commercial inputs must be completely depleted before the state of nature is realized.

Furthermore, both farmers and creditors are assumed to be risk-neutral, with separable preferences over money and the possession of the contracted land. The farmer's one-period profit function from production takes forms (4) and (5) under the conventional and hi-tech alternatives, respectively:

$$(4)\quad \begin{cases} q \cdots \text{w/probability } 1 - p^c, \\ 0 \cdots \text{w/probability } p^c, \end{cases}$$

and

$$(5)\quad \begin{cases} f(K) - K(1 + r_h) \cdots \text{w/probability } 1 - p^h, \\ -K(1 + r_h) \qquad \cdots \text{w/probability } p^h, \end{cases}$$

where r_h is the interest rate for the risky investment of the creditor, $r_h > r_s$. The production and borrowing recur each year depending on the risks, and losing the land will result in foregoing all future profits. Therefore, the present values of the land for farmers are then given by (6) and (7), respectively.

$$(6)\quad W^c = \sum_{t=1}^{n} (1 + r)^{-t} \times \begin{cases} V \qquad \cdots \text{w/probability } p^c, \\ V + q \cdots \text{w/probability } 1 - p^c, \end{cases}$$

where V denotes the additional value the farmer perceives from having the land use rights for one period, measured at the end of the period.[2] The expected present value of wealth under the conventional technology is:

[2] This value is rather subjective, consisting of primarily nonagricultural use value. It may include the sense of security, social prestige in the community (Bell and Clemenz, 2006), and even speculative opportunity for future urban development. The last source of value is supported by the practice that urban development compensation to landless farmers is often proportional to the contracted acreage under HRS. Without a secured form of land use rights, this value does not exist.

$$(7)\quad EW^c = \sum_{t=1}^{n}(1+r)^{-t}\left[V+q(1-p^c)\right] = \frac{\left[V+q(1-p^c)\right]\left(1-(1+r)^{-n}\right)}{r},$$

$$(8)\quad W^h = \begin{cases} 0 & \text{w/prob. } p^h, \\ [V+f(K)-K(1+r_h)](1+r)^{-1} & (1-p^h)p^h, \\ [V+f(K)-K(1+r_h)] & \\ \quad\times[(1+r)^{-1}+(1+r)^{-2}] & (1-p^h)^2p^h, \\ \vdots & \\ [V+f(K)-K(1+r_h)] & \\ \quad\times[(1+r)^{-1}+\ldots+(1+r)^{-n}] & (1-p^h)^n. \end{cases}$$

The implicit assumption here is that under production failure, the farmer has no other resource to pay off the debt and must face a foreclosure—i.e., giving up the land use rights to the creditor. Then, s/he not only loses future revenues from cultivating the land, but also the additional value that is attached to the land use rights.

The welfare optimum decision for a risk-neutral farmer is determined by model (9), because the conventional technology is the farmer's reservation:[3]

$$(9)\quad \underset{K}{\text{Max}}\, EW^h = \frac{\left[1-(1-p^h)^n(1+r)^{-n}\right](1-p^h)}{r+p^h} \times\left[V+f(K)-K(1+r_h)\right],$$

$$\text{s.t.:}\quad \frac{\left(1-(1+r)^{-n}\right)}{r}\left[V+q(1-p^c)\right] < \frac{\left[1-(1-p^h)^n(1+r)^{-n}\right](1-p^h)}{r+p^h} \times\left[V+f(K)-K(1+r_h)\right].$$

According to this model, the farmer will choose the level of investment, which is also the mortgage loan size, on the hi-tech production to maximize his or her welfare as long as this welfare is higher than that from the conventional production. The welfare is defined as ex ante expected present value of profits from production over the n years. Otherwise, the farmer will choose to stay in conventional farming and not take the loan.

Without the constraint, the first-order condition, $f'(K^*) = 1 + r_h$, requires that the marginal output of capital be equal to one plus the interest cost. So, the optimal production level, K^*, is independent of the opportunity cost of capital, probability of failure in either technology, return from the conventional technology, or subjective value of the land. The higher the interest rate the creditor requests from the farmer, the lower the level of the loan and production (Figure 1). The loan size can be different for borrowers depending on their individual production efficiency (production functions).

The constraint requires the optimal value of per period profit under the successful state of nature to be greater than

$$\frac{(r+p^h)\left(1-(1+r)^{-n}\right)}{(1-p^h)r\left[1-(1+r)^{-n}(1-p^h)^n\right]} \times\left(V+q(1-p^c)\right) - V.[4]$$

This function (the intercept of the horizontal line in Figure 1) is increasing in V, qp^h, but decreasing in r and p^c. Therefore, if the farmer has (*a*) a high subjective value of the ownership of the land use rights, (*b*) a high profit in conventional production, (*c*) a high probability of failure under the hi-tech production, (*d*) a low opportunity cost of capital, and/or (*e*) a low probability of failure in conventional production, s/he tends to stay away from the hi-tech production and loan to avoid the risk of production failure resulting in foreclosure.

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[3] The equal sign is removed from the constraint because in that case the farmer simply stays with conventional technology.

[4] This is obtained by multiplying the positive number

$$\frac{(r+p^h)}{(1-p^h)[1-(1+r)^{-n}(1-p^h)^n]}$$

on both sides of the constraint inequality and then subtracting V from both sides.

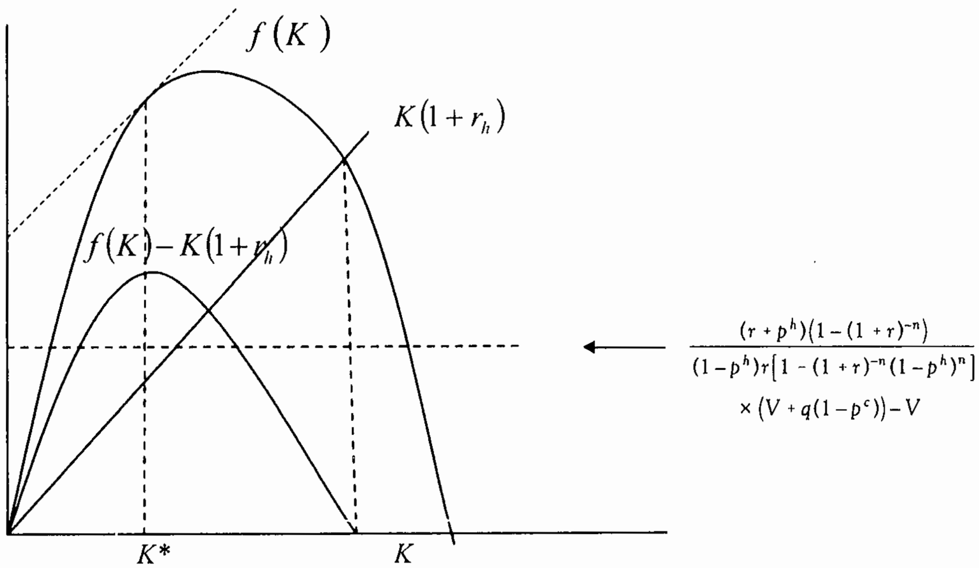

Figure 1. The Optimization of Production Under Hi-Tech

The opportunity cost of not taking the hi-tech option is not so high compared to the conventional production.

The creditor can loan the money to the farmer or invest it in a risk-free asset to earn a net return of Kr_s. When providing the hi-tech production loan to a farmer, the creditor faces a risky net return of either Kr_h, or $-K$ with a probability of p^h without a mortgage. The expected break-even interest rate the creditor needs to charge in the absence of a land mortgage is determined by:

$$(10) \quad r_s K = r_h(1-p^h)K \quad \text{or} \quad r_h = \frac{r_s}{1-p^h}.$$

It will be either too risky for the creditor if the interest rate is not high enough, or too expensive for the farmer if the interest rate is set too high, resulting in a market failure in Chinese rural finance. The lack of rural credit is a commonly observed problem, and producers are trapped in the conventional technology with the low level of expected welfare, EW^c. As noted by Cao (2006), many rural households in China stay in simple production each year without any expansion or improvement due to a lack of finance. Now with the mortgage, the creditor obtains the land use rights in case the borrower cannot repay.

If M, the market value of the land use rights, less the transaction cost[5] is high enough to cover the entire loan during foreclosure, then the risk left for the creditor is considerably lower, and so is the loan interest rate. The market value of the land use rights can be realized through selling the certificate or leasing the land under long-term contract to other farmers in the area.

The demand for such land use rights exists because in general the current land size of each farm is very small and additional land will contribute to profitability. The new Property Law allows subleasing from the current certificate owner, and such subleasing is observed in China.

During a production failure, there is usually some loss on the creditor's side, either through a high transaction cost or low market price for the land use rights; thus, the creditor does not prefer this loan to other risk-free investment opportunities. Therefore, the creditor sets a slightly higher interest rate to break even

[5] The transaction cost refers to the creditor's administrative cost during foreclosure.

between investing in risk-free and hi-tech agricultural production. This can be shown by the creditor's break-even revenue in (11):

$$(11)\quad r_s K = r_h\left[p^h M + (1-p^h)K\right].$$

If we denote the ratio of net market value of the land use rights to the loan size by $m = M/K$, the interest rate for the mortgage loan offered by the creditor is:

$$r_h = \frac{r_s}{1-p^h(1-m)}.$$

For $m < 1$, $r_h > r_s$. The higher the probability of failure in hi-tech, and/or the lower the ratio of net market value of the land use rights to the loan size, the higher will be the interest rate charged. However, this rate is lower than the case without the mortgage as in (10), as long as $M > 0$. Notice, the absolute value of the loan size, K, does not affect the creditor's choice of interest offer.

The farmer's welfare gain from having the tradable land use rights can be derived from equations (7) and (9) as $EW^h - EW^c$ in (12):

$$(12)\quad \frac{E\left[1-(1-p^h)^n(1+r)^{-n}\right](1-p^h)}{r+p^h} \times\left[V+f(K)-K(1+r_h)\right] - \frac{\left(1-(1+r)^{-n}\right)}{r}\left[V+q(1-p^c)\right],$$

where $r_h = r_s/[1-p^h(1-m)]$. The welfare gain on the creditor's side is the entire expected business profit from providing the mortgage loan.

Some borrowers may deliberately default, because they either do not value the land use rights, they have other profitable business opportunities, or they desperately need the money. In this case the creditor's break-even interest rate can reach its highest level, $r_h = r_s/m$, when everyone defaults. Again, with information asymmetry, creditors either lose money or the interest rate is set high.

Different Risk Levels and Borrowers' Adverse Selection

In this section, the case of heterogeneous producers and asymmetric information is discussed. Suppose there are two types of farmers: one with high risks under hi-tech production and the other low. If the creditor has full information and can differentiate borrowers by their risk levels, different interest rates for the mortgage loans can be charged, and the growers' model in (9) can be solved for each type of farmer separately. In reality, the creditor may not be able to differentiate the two types of borrowers and must charge a uniform rate, r_h, as calculated in the previous section, assuming there are equal shares of each type of farmer in each group.[6]

Referring again to Figure 1, the two curves and the cost line remain the same for both types of farmers, but there are two constraint lines horizontally. The lower- (higher-) level line represents the low- (high-) risk farmers. If production efficiency (function curves) is also not homogeneous, some less efficient but also less risky farmers will still choose the conventional technology. Actually, some of them could have chosen the hi-tech alternative if the creditor could differentiate and charge them a lower rate. Also, due to the higher interest rate, the size of the loan and the scale of the production are smaller. Compared to the case of perfect information, both effects contribute to a welfare loss due to imperfect information.

The upper-level constraint line designates the high-risk farmers. The constraint might not hold at the optimum, and many, if not all, high-risk farmers should choose the conventional production and will not take the loan. However, because the interest rate charged is lower for high-risk borrowers than otherwise if the creditor

[6] Any ratio can be assumed by taking a weighted average of high and low probabilities of failure. The discussion below should still hold.

can differentiate the two types of borrowers, some high-risk growers can take the loan. High-risk farmers also have larger loans and higher levels of production, resulting in a slight expected welfare gain. Still, this gain is at the cost of those low-risk farmers who should have been charged a lower interest rate and taken a larger loan size to promote higher production levels. Compared to the homogeneous risk case, although it is hard to determine whether the asymmetric information contributes to the aggregated farmers' expected welfare gain or loss ex ante, certainly this scenario attracts some high-risk growers into the loan and detracts some low-risk growers away from the loan. Consequently, this will result in more failure and foreclosure, a welfare loss ex post.

As for the creditor, although s/he loses some borrowers and gains others, those who are lost have low risks but the ones gained have high risks. This makes the creditor's overall average risk higher than the original planned average from the whole group. When the loan size is smaller for low-risk borrowers and larger for high-risk borrowers, the weighted average of risk will be higher. Therefore, the creditor has a welfare loss when s/he cannot differentiate the two risk types of borrowers. This is the effect of adverse selection.

The adverse selection effect on the creditor can be more severe if some farmers strategically choose the loan and default. More of those farmers with low subjective value of the land use rights may come from the high-risk group, with higher production risks in both conventional and hi-tech practices. In contrast, low-risk and high-efficiency producers may have other profitable opportunities for using the land (choosing to stay away from the mortgage loan) or not using the land (choosing the loan and defaulting). Neither case is favorable to the creditor. Therefore, the creditor needs to provide smaller loans relative to the market value of the collateral and scrutinize borrowers.

As commonly used in financial markets, borrowers' characters, credits, and collaterals (CCC) are checked carefully by creditors. Now that collateral is established, the other two C's also should be examined. Learning from the currently existing informal rural finance, the creditor can use community involvement and rate farmers' credits based on trust and social characters. With this additional information to categorize farmers into high- and low-risk groups, two or multiple separate interest rates can be charged. The production curves and cost lines in Figure 1 are then separated for the two or multiple groups of farmers. Farmers in each risk group will have a different optimum production level. Although the perfect information about farmers' credit risks is difficult to obtain, using supporting information from the community will reduce the harmful effects on the credit market from information asymmetry and adverse selection.

The Creditor's Desire for the Land

As has been discussed in the literature, creditors may have a desire for the land (Bell and Clemenz, 2006). Some moneylenders may be more efficient farmers or agribusinesses and have interests in land. Especially in cases when farmers are extremely reluctant to sell the land use rights at a price close to the present value of future income flows, this is almost the only way for lenders to acquire the land use rights at an acceptable price.

It is hard to justify that commercial creditors would desire the disaggregated small plots of farmland "here and there" in China. Urban development in suburban areas usually competes with agricultural production for large plots of land. It is unrealistic to assume an entire neighborhood would take a loan and end up with foreclosure. Also, the conversion of agricultural land for nonagricultural use is restricted. However, if the creditors are from informal channels—such as neighboring farms, local nonfinancial businesses, or other local credit sources—they may have a special interest in the land and place a higher value on it. This value can be derived from agricultural production for higher valued commodities, recreational use, agribusiness use, speculation in resale or rental, and/or a sense of land ownership.

In China currently, where the formal and legal rural financial market is underdeveloped, there exists a quite active informal credit market.[7] In this case, the creditor may lower the interest rate charged to the borrower until

$$(13)\quad r_s K = r_h\left[p^h(M+U)+(1-p^h)K\right].$$

The only difference between the solution here, $r_h = r_s/[1 - p^h(1 - m - u)]$, and that in (11) is the introduction of u, $u = U/K$, the ratio of the creditor's special value on the land relative to the size of the loan. However, the additional term can make the denominator larger than one, and the interest rate charged at or below the market risk-free rate of interest. The effect would be that more previous conventional producers would now be converting to hi-tech production and taking loans. The risk of foreclosure is much higher for the borrowers as a group, which is just what the creditor desires.

Even under the case of heterogeneous producers, because the loan interest rate is lower, there are more producers taking the loan option in each group. However, because of different risk levels, it is those in the high-risk group who tend to lose their land first. This is a way to transfer the land use rights from the high-risk and inefficient producers to those with a higher value on the land. If the value U is derived from other agricultural production activities discussed above, it means the land transfers to low-risk and efficient producers, resulting in an expected welfare increase for the economy.

Individual-level loss will occur to the high-risk producers if they can't fully comprehend the consequences of a mortgage when making the loan decision. Based on the theoretical model that producers have full information about their risks and make rational decisions based on the expected profit maximization when facing an exogenous interest rate, their ex ante expected welfare is still improved upon when such loans are not available or are available at a higher interest rate. Other risk management measures, such as production insurance or off-farm income opportunities, need to be considered by this type of producer to avoid and mitigate ex post welfare loss.

Concluding Remarks and Policy Implications

In this paper, we first discussed the possibilities for China to allow market transferability of farmland use rights in the form of tradable certificates, and then developed a producer's wealth maximization model when the production is risky and mortgage loans based on land use rights are available. Cases considered include no mortgage contract, risk-free production, homogeneous producers with a mortgage contract under risk, heterogeneous producers with adverse selection under information asymmetry, and the creditor's desire for the land. Welfare effects were discussed for these alternative cases.

The theoretical results show that the introduction of mortgage loans will improve the welfare and expected welfare (under risk) of agricultural producers in every case. For producers with homogeneous risk levels, without any hidden information, those with higher production efficiency, higher opportunity cost of capital, lower return from conventional technology, and lower subjective value on the land tend to take

[7] This is a different scenario than recently reported in China where some illegal agents provide mortgage loans to borrowers at interest rates that are not low at all. Equation (8) is under the competitive financial market. While in China such a market does not exist, those illegal agents can set high interest rates.

the mortgage loan. The size of the loan is solely determined by their production function and the interest rate.

When producers are heterogeneous in risks and the creditor cannot differentiate them (asymmetric information), it leads to adverse selection of borrowers with fewer low-risk borrowers and more high-risk borrowers than if the creditor can set different rates for different types of borrowers (a welfare loss compared to the perfect information case). However, this scenario still shows welfare improvement over the no mortgage loan case.

When the creditor has an additional value from the land, s/he will establish lower interest rates to induce more borrowers and more foreclosure cases, especially when the market is thin for direct purchase. In this case, the creditors and borrowers still have higher ex ante welfare even if more end up in foreclosure, as long as the decisions are made under full information about their own risks. Still, the risk can cause severe ex post welfare loss, especially to high-risk producers. Farmers need to be educated as to the real possibility of land loss through mortgage loans, and they also need to undertake risk management measures.

The efficiency contribution of HRS to Chinese agriculture was extraordinary at the beginning of China's economic reform. However, the farmland fragmentation and lack of finance have prevented further efficiency improvement from modern management technologies mostly requiring scales and credits.

Sustainable development in agriculture calls for policies dealing with land ownership or use rights tradability. Currently, leasing and subcontracting of land use rights are permitted and encouraged in rural China. While these strategies can alleviate the land fragmentation problem to a certain degree, they are not applicable for long-term land improvement investment. Market-based transfer of land and land use rights is an ultimate alternative.

Allowing land use rights as mortgage collateral will contribute to production efficiency and improved welfare through hi-tech adoption, when land itself remains publicly owned. Mortgage loans may result in land use rights transfers and aggregation, but they are not necessarily correlated to poverty. Farmers are advised to be aware of the production risk and the possibility of loss of land use rights when taking a mortgage loan. Risk management instruments, nonfarm employment opportunities, and social welfare are also needed to support the land use rights transferability.

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Earnings, Accruals, Cash Flows, and EBITDA for Agribusiness Firms

Carlos Omar Trejo-Pech, Richard N. Weldon, and Lisa A. House

Abstract

This study examines empirical relationships of earnings, accruals, and cash flows for the U.S. food supply chain sector (i.e., agribusiness) and compares them with results for the complete U.S. market. In addition, we evaluate earnings before interest, taxes, depreciation, and amortization (EBITDA) as a potential proxy for cash flow. Empirical results show that while earnings and accruals are systematically positively related, accruals and cash flows are systematically negatively related. Moreover, both the magnitude and the behavior of EBITDA across different levels of cash flows for agribusinesses do not mimic cash flows. Thus, this metric is not a valid proxy for cash flow in accrual research studies.

Key words: accruals, agribusiness, cash flows, earnings, EBITDA, financial accounting

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Recent research suggests that investors and financial analysts systematically fail to fully interpret relevant information revealed on firms' financial statements. The empirical tests carried out in this study are built on this premise. The accrual anomaly problem, initiated in work by Sloan (1996), is the main framework used to analyze agribusinesses.

Importance of Accruals

Accruals are the difference between earnings and cash flow. Earnings and cash flow differ because accounting principles with respect to the timing and magnitude of revenues and expenses are not necessarily based on cash inflows and outflows. It is commonly accepted that the use of accruals accounting, as opposed to cash-based accounting, improves the ability of earnings to measure firm economic performance (Revsine, Collins, and Johnson, 2005). In agriculture, the Farm Financial Standards Council,[1] for instance, has been promoting the use of accruals accounting.

Ellinger (1999) illustrates the importance of accruals-based accounting in agriculture using a sample of 1,084 farms in Illinois over the period 1995–1997. His findings suggest that the differences between cash and accrual earnings, averaging up to 44% for farms in the upper quartile ranked by the absolute percentage difference, make it difficult for lenders to evaluate farms that use cash as a proxy for earnings. Ellinger shows that adjusting cash income by

[1] Refer to *Financial Guidelines for Agricultural Producers*, revised December 1997, available online at www.ffsc.org.

changes in inventories (a step toward a measure of cash flows from operations) reduces the discrepancies between cash and earnings, encouraging borrowers to start using accruals-based information.

The accounting accrual process created to mitigate the timing problems of cash-based accounting is mainly guided by two accounting principles—the revenue recognition principle and the matching principle.[2] This allows Dechow (1994, p. 4) to posit that the primary role of accruals "is to overcome problems with measuring firm performance when firms are in continuous operation."

Unfortunately, the use of accruals-based accounting introduces a new set of problems, largely due to the discretion that management has over the recognition of accruals. This results in a tradeoff between earnings and cash flow as relevant metrics for summarizing firm performance. To the extent that managers use their discretion to opportunistically manipulate accruals, earnings become a less reliable measure of firm performance and cash flows could be preferable. Consequently, the net effect of accruals becomes an empirical question of importance. Do accruals improve or reduce the ability of earnings to measure firm performance? What are the systematic relationships, if any, among earnings, cash flows, and accruals? What is the relationship between accruals and stock returns? These questions are of interest in this study, particularly for agribusinesses.

Data

The main data are annual financial statements obtained from the industrial active and research files of Standard & Poor's Compustat North America and monthly stock price data from the Center for Research in Security Prices (CRSP) at the University of Chicago. The sample is restricted to domestic agribusinesses (i.e., firms belonging to the food supply chain) available in the two databases (merged CRSP/Compustat).[3] The use of only domestic firms means the elimination of American Depository Receipts (ADRs) and agribusinesses incorporated outside the United States. This filtering of the sample is standard in empirical studies in finance and accounting. Also consistent with previous studies, only firms trading on the New York Stock Exchange, the American Stock Exchange, and NASDAQ are considered, thus excluding firms traded only in regional markets.

The principal empirical tests cover a 35-year time span (1970–2004). Data on Compustat (CRSP) start in 1950 (1925 for NYSE stocks); however, in selecting the sample period for this study, the data screening process was only performed for 1962–2005. Pre-1962 data were not considered given that Fama and French (1992) found pre-1962 data in Compustat to suffer from serious selection bias toward historically successful firms. After completing the data screening, 1962–1969 data were eliminated from the sample due to the relatively small number of agribusinesses with data available for these years.[4] With regard to the ending year, the 2006 version of CRSP is used in the study, but since the computation of "future" annual returns requires data from at least one year ahead, and returns are calculated starting four months after the firm's fiscal year end, the ending period for the study is 2004.

[2] Revenues are recognized when both the critical event in the process of earning the revenue has taken place (i.e., the revenue is earned even though it has not been collected), and the amount of the revenue that will be collected is reasonably assured and is measurable. Corresponding expenses are recognized during the same accounting period when the revenue is recognized.

[3] Research files in these data sets, as opposed to active files, contain data on firms that are no longer actively trading in a stock market for reasons such as forced delisting, merger, acquisition, bankruptcy, etc. In other words, firms are not required to survive through the period of study to be included in the sample.

[4] Few firms per year would be restrictive for the formation of portfolios. In particular, those years with less than 100 agribusinesses were eliminated from the sample.

The Food Supply Chain

The U.S. Department of Agriculture's (USDA's) Economic Research Service (ERS) provides a classification of farm and farm-related industries based on Standard Industrial Classification (SIC) codes. This classification identifies industries that have at least 50% of their national work force employed in providing goods and services to satisfy the final demand of agricultural products. Industries are classified into six major groups: (*a*) farm production; (*b*) agricultural services, forestry, and fishing; (*c*) agricultural inputs; (*d*) agricultural processing and marketing; (*e*) agricultural wholesale and retail trade; and (*f*) indirect agribusiness. These major groups are composed of 30 subgroups and more than 80 four-digit SIC industries. (For interested readers, a complete classification is available on the ERS website.)

Two major industry groups are selected for this study: (*a*) agricultural processing and marketing (henceforth food processing and beverage), and (*b*) agricultural wholesale and retail trade (henceforth food wholesale, retail, and service). The remaining groups are excluded from the sample due to their relatively small number of firms.[5] Within the two major groups some additional screening was necessary. The final sample includes 13 three-digit SIC industries, 10 belonging to the food processing and beverage major group and 3 to food wholesale, retail, and service.[6]

Consequently, the food supply chain in this study includes processors, wholesalers, retailers, and food service providers. This categorization of the food supply chain is similar to that reported in previous studies throughout the agribusiness literature (e.g., Rogers, 2001; USDA/ERS, 2002; Schumacher and Boland, 2005).

Final Sample

To be included in the sample, an agribusiness firm-year should contain sufficient information in Compustat to compute all financial statement variables (defined in the Empirical Measurement section) and in the CRSP monthly returns file to compute buy-and-hold annual returns (details in the Stock Returns section below). The final merged CRSP/Compustat sample contains 8,553 firm-year observations for the 1970–2004 period. The sample is broken down by industries and years (see Appendix Table A2), with 48.5% of the observations belonging to the food processing and beverage major industry group, and 51.5% to the food wholesale, retail, and service industry group.

Stock Returns

Stock returns are buy-and-hold returns calculated as

$$BHR_{i,t} = \prod_{j=1}^{12} \left(1 + r_{i,j}\right) - 1,$$

where $BHR_{i,t}$ is the buy-and-hold compound annual return for firm i in year t, and $r_{i,j}$ is the CRSP monthly rate of return inclusive of dividends and all other distributions over month j. Year refers to fiscal year as defined in Compustat.

The return cumulation period starts four months after the end of the agribusiness' fiscal year (i.e., four-month waiting window). For instance, for a firm with an October fiscal year reporting financial statements in 2002, the buy-and-hold return period is March 2003 to February

[5] Inspection of raw data in Compustat for the 1995–2005 subperiod, for instance, indicates that the major groups excluded from the sample have around 20 firms per year, while both the food processing and beverage industry and the food wholesale, retail, and service industry have at least 150 firms each.

[6] Certain industries within this group were not included in the sample (such as apparel and textiles; leather products and footwear; warehousing; packaging; and farm-related raw materials) due to the small number of firms in the data sets or a lack of similarity compared with the food, drink, and tobacco industries.

2004.[7] Thus, returns reported are buy-and-hold annual rate of returns for year $t+1$, following financial statements reported in year t. We report $t+1$ fiscal year aligned returns instead of t since the research deals with the implication of accounting data reported in time t and market reaction in $t+1$.

The four-month waiting window referred to above is common in the literature of empirical work related to accruals (e.g., Lakonishok, Shleifer, and Vishny, 1994; Sloan, 1996; Chan, Karceski, and Lakonishok, 1998; Richardson et al., 2005; Chan et al., 2006; Hodder, Hopkins, and Wood, 2006), thereby allowing for the delay between the end of the fiscal year and when the accounting information becomes publicly available to all investors in practice (Alford, Jones, and Zmijewski, 1994). This empirical implementation makes it more likely that accounting variables are available before the returns they are used to explain.

Model of Accruals

Accounting earnings can be represented as the sum of two components: accruals and cash flow. The mapping of accruals, cash flow, and earnings in the context of the balance sheet could be modeled following Dechow (1994) with some modifications.[8] Appendix Table A1 provides selected items of financial statements and their respective item numbers in Compustat to illustrate the discussion that follows. By the basic accounting equation, assets equal the sum of liabilities and equity in any point in time:

(1) $\Delta Assets = \Delta Liabilities + \Delta Equity.$

Categorizing assets into cash and noncash items, categorizing both assets and liabilities into current and long-term items, and recognizing that the change in equity ($\Delta Equity$) can be expressed as the change in contributed capital plus the change in retained earnings, we have:

(2) $$\Delta Cash + \Delta NCCA + \Delta NCLTA = \Delta CL + \Delta LTL + \Delta CC + \Delta RE,$$

where $\Delta Cash$ represents the change in cash from period to period, $\Delta NCCA$ is the change in noncash current assets, $\Delta NCLTA$ is the change in noncash long-term assets, ΔCL is change in current liabilities excluding debt, ΔLTL is change in long-term liabilities plus change in short-term debt, ΔCC is change in contributed capital, and ΔRE is change in retained earnings.

Further, the change in retained earnings can be expressed as earnings minus paid dividends, and both the change in long-term liabilities (ΔLTL) and the change in noncash long-term assets ($\Delta NCLTA$) can be broken down into those accounts affecting and not affecting cash. For instance, borrowing and repayment of long-term debt relate to liabilities affecting cash. Similarly, purchases or sales of long-term assets relate to noncash long-term assets affecting cash, while depreciation is related to noncash long-term assets and does not affect cash. Rearranging, the model is written as:

(3) $$\Delta Cash = \underbrace{Ear + \underbrace{\Delta CL - \Delta NCCA}_{a} + \underbrace{\Delta LTL_{NC} - \Delta NCLTA_{NC}}_{b}}_{\text{Cash Flow from Operations}} \underbrace{- \underbrace{\Delta NCLTA_{C}}_{c} + \underbrace{\Delta LTL_{C} + \Delta CC - Div}_{d}}_{\text{Cash Flow from Investing \& Financing}},$$

where Ear is earnings, ΔLTL_{NC} is the change in long-term liabilities not affecting

[7] Most of the variables of interest in this study are provided in Compustat on a fiscal-year basis as opposed to calendar year. In Compustat, fiscal years ending January through May are treated as ending in the prior calendar year, and fiscal years ending June though December are treated as in the current year. Annual returns were compounded matching CRSP monthly returns accordingly (considering the four-month waiting window) to each agribusiness' fiscal year in Compustat.

[8] Dechow (1994) implicitly assumes zero short-term debt. Short-term debt is included in this model. Also, the exposition here differs from Dechow's.

cash, $\Delta NCLTA_{NC}$ is the change in noncash long-term assets not affecting cash, ΔLTL_C is the change in long-term liabilities affecting cash, $\Delta NCLTA_C$ is the change in noncash long-term assets affecting cash, *Div* is dividends, and all other variables are as defined previously.

The structure of (3) illustrates the connections between the balance sheet and the statement of cash flow. Changes in working capital are represented by *a* in (3), while *b* represents change in long-term accounts not affecting cash such as depreciation and other noncash adjustments in cash flow from the operations section of the statement of cash flow; *c* aggregates cash flow from investing activities, and *d* represents cash flow from financing.

Renaming the change in cash ($\Delta Cash$) as simply cash flow (*CF*),[9] (3) can be reexpressed as:

$$(4) \quad Ear - CF = \Delta NCCA - \Delta CL + \Delta NCLTA_{NC} - \Delta LTL_{NC} + \Delta NCLTA_C - \Delta LTL_C - \Delta CC + Div,$$

where the right-hand side of (4) is accruals (*Acc*).[10] *Acc* represents the net change in the balance of all noncash accounts and measures all adjustments made when an accruals basis of accounting is used as opposed to cash-based accounting.

Empirical Measurement

The measurement of accruals in empirical studies, begun by Healy (1985) and later employed by Sloan (1996), links earnings and cash flow *from operations*. In the current empirical literature, "accruals" is measured assuming *c* and *d* in (3) are equal to zero. One exception is in Richardson et al. (2005), where "total accruals" is measured as opposed to accruals. Thus, the term "accruals" as used in the literature and in this study refers to current accruals.

Balance Sheet Accruals

Accounting earnings (*Ear*) represents the sum of two components: a cash flow and an accrual component. Cash flow (*CF*) could then be expressed as:

$$(5) \quad CF = Ear - Acc,$$

where *Ear* is earnings and *Acc* is accruals. *Ear* is measured by operating income after depreciation (Compustat item 178) divided by average total assets, the average of beginning and ending book value of total assets (item 6). Some empirical studies use a different measure of earnings [e.g., Freeman, Ohlson, and Penman (1982) use net income; Dechow (1994) and Moehrle, Reynolds-Moehrle, and Wallace (2003) use net income excluding extraordinary items and discontinued operations].

The main empirical work related to accruals referred to in this paper uses operating income as the measure of earnings. Operating income excludes non-recurring items such as extraordinary items, discontinued operations, special items and non-operating income, taxes, and interest expenses. We measure accruals following Sloan (1996) and Chan et al. (2006). Sloan measures accruals as follows:

$$(6) \quad Acc = \Delta NCCA - \Delta NCCL - DA,$$

where $\Delta NCCA$ is change in noncash current assets defined as the change in current assets (Compustat item 4) minus the change in cash and short-term investments (item 1); $\Delta NCCL$ is the change in current liabilities excluding debt and taxes payable and is defined as the change in current liabilities (item 5) minus the change in short-term debt (item 34) and minus the change in income taxes payable (item 71); and *DA* is depreciation and

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[9] One can think of *CF* as cash generated in a given period ignoring cash available at the beginning of the period (i.e., assume zero cash at the beginning) in this context, and as referred to in the literature.

[10] Deschow (1994) refers to this as "aggregated accruals."

amortization (item 14). All variables are divided by average total assets (item 6).[11]

Chan et al. (2006) further decompose Sloan's empirical measurement of accruals:

$$(7) \quad Acc = \Delta AR + \Delta INV + \Delta OCA - \Delta AP - \Delta OCL - DA,$$

where ΔAR is change in accounts receivable (item 2), ΔINV is change in inventories (item 3), ΔOCA is change in other current assets (item 68), ΔAP is change in accounts payable (item 70), ΔOCL is change in other current liabilities (item 72), and DA is depreciation and amortization (item 14). All components are divided by average total assets (item 6).

Measuring accruals using equation (7) incurs the cost of eliminating some observations from the database with missing values. However, this provides additional insights. Results in this study are reported at both levels of decomposition whenever appropriate.

As indicated above, all variables are divided by average assets to control for scale differences. Sloan (1996) initiated the use of average assets to scale accruals. Alternative investment bases have been explored including sales, beginning-of-period assets, end-of-period assets, book value of net assets generating the accruals, and market capitalization.[12] Results have been reported to be insensitive to the choice of investment base (Healy, 1985; Sloan, 1996), and average total assets is currently used in the accruals literature.

[11] Accruals are computed for each agribusiness every year. For convenience, firm and time subscripts are omitted for accrual equations in this study.

[12] Book value of net assets generating the accruals is net operating assets, which is problematic for the empirical tests due to negative values that are not uncommon in firms in this sample such as food stores. Market capitalization, an alternative deflator, might also become problematic if accruals are studied in relation to firms' market returns due to the contemporaneous relation of market capitalization and stock prices.

Statement of Cash Flow Accruals

Equations (6) and (7) model accruals using the balance sheet. This approach assumes full articulation between changes in balance sheet working capital accounts and the accrual component of revenues and expenses on the income statement. We refer to balance sheet accruals or simply "accruals" whenever this approach is used. Alternatively, we measure accruals from the statement of cash flows following Hribar and Collins (2002):

$$(8) \quad Acc_{CF} = EBXI - CFO + EIDO,$$

where Acc_{CF} is statement of cash flow accruals, *EBXI* is earnings before extraordinary items and discontinued operations (Compustat item 123), *CFO* is cash flow from operations (item 308), and *EIDO* is extraordinary items and discontinued operations (item 124), which is a cash portion added back to obtain a cash flow from *continuing* operations, consistent with the definition of earnings. All items are divided by average total assets (item 6).

Hribar and Collins (2002) find that the use of the balance sheet may introduce errors into the measurement of accruals primarily due to mergers, acquisitions, and divestitures. They argue that the presumed articulation between changes in balance sheet working capital accounts and the accrual component of revenues and expenses on the income statement breaks down in the presence of non-operating events such as mergers, acquisitions, and divestitures, and that such potential errors may be reduced when statement of cash flow accruals is used instead of balance sheet accruals. Hribar and Collins (pp. 107–108) state, "changes in current assets and liabilities due to these non-operating events show up in the balance sheet, but do not flow through the income statement. Consequently, a portion of the charges in balance sheet working capital accounts relates to the non-operating events, and would erroneously be shown as accruals under the balance sheet approach."

This implies that firms following mergers and acquisitions are more likely to be categorized as firms with high accruals. Conversely, firms divesting operations are more likely to be categorized as firms with low accruals, and their subsequent stock return may be associated with this fact rather than with operating performance, which is the main interest in studies on accruals.[13]

The suggestion by Hribar and Collins (2002) to use statement of cash flow accruals as opposed to balance sheet accruals has been echoed in the accruals literature, but apparently the cost of implementing this approach outweighs the advantages. Data availability seems to be one of the limitations since statement of cash flows data are available only starting in 1988, while most of the data needed to estimate balance sheet accruals are available since 1950. Thus, while in recent studies the findings by Hribar and Collins are acknowledged in market mispricing of accruals applications (e.g., LaFond, 2005; Richardson et al., 2005; Kothari, Loutskina, and Nikolaev, 2006; Chan et al., 2006), main tests on those studies are reported under the balance sheet approach (one exception is Kraft, Leone, and Wasley, 2006). Alternative tests using statement of cash flow accruals are mentioned as robustness checks ensuring similar quality of results.

In this study we employ both approaches to estimate accruals. The main results are reported using balance sheet accruals. Our research is more sensitive to sample reduction than previous studies since it is limited to food supply chain firms, a subsample of previous studies covering all but financial U.S. firms (availability of data to measure Acc_{CF} reduces the sample from 8,553 to 4,071 firm-year observations). However, we find it necessary to test the validity of EBITDA as a proxy for cash flow using statement of cash flow accruals as opposed to balance sheet accruals (this rationale is explained in the corresponding section of the test).

Results

Earnings and Its Components

Working capital is analyzed at the outset since changes in working capital constitute the core of accruals and the literature frequently conditions results on accruals to be industry specific. Summary statistics of the main components of operating working capital, components of earnings, and components of accruals for the U.S. food supply chain compared to results for the complete U.S. market ("all the U.S. market") from a previous study by Chan et al. (2006) are provided in Table 1.

Panel A in the table shows working capital accounts (current assets and current liabilities), and components of operating working capital (accounts receivable, inventories, and accounts payable), all divided by average total assets. For the U.S. market, accounts receivable and inventories represent the most important magnitudes of working capital components, with respective means of 0.217 and 0.218. The food supply chain has a working capital structure similar to that for the market with the exception of the size of accounts receivable (0.122 mean), which is almost half that of the market (0.217 mean), with coefficients of variation of 0.841 and 0.645, respectively. Further decomposition of this account reveals that the low level of accounts receivable is mainly driven by the food wholesale, retail, and service major industry, which has a mean of 0.084 compared to 0.164 for the food processing and beverage major industry.

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[13] Mergers and acquisitions bias accruals upward under the balance sheet approach as net current assets increase (i.e., accounts receivable and inventories increase in the merger firm). The opposite occurs with divestitures (downward bias). The direction of the bias introduced by other non-operating events analyzed by Hribar and Collins (2002) is more difficult to predict (for instance, foreign currency translation).

Table 1. Descriptive Statistics of Earnings, Cash Flow, Accruals, and Working Capital for the U.S. Food Supply Chain and the Complete U.S. Market

	U.S. Food Supply Chain		All the U.S. Market	
Description	**Mean**	**CV**	**Mean**	**CV**
PANEL A. Working Capital and Components [a]				
Current Assets	0.418	0.484	0.459	0.519
Current Liabilities	0.267	0.515	0.191	0.576
Accounts Receivable	0.122	0.841	0.217	0.645
Inventories	0.196	0.440	0.218	0.780
Accounts Payable	0.123	0.702	0.103	0.796
PANEL B. Earnings and Components [b]				
Accruals	−0.044	−2.130	−0.012	−8.500
Cash Flows	0.139	1.073	0.133	1.060
Earnings	0.094	1.394	0.121	1.041
PANEL C. Accruals Components [c]				
$\Delta NCCA$	0.028	3.634	0.060	2.017
$\Delta NCCL$	0.019	3.776	0.027	2.370
DA	0.053	0.472	0.045	0.622
ΔAR	0.010	5.270	0.030	2.433
ΔINV	0.015	4.040	0.026	2.731
ΔOCA	0.003	14.497	0.004	5.750
ΔAP	0.011	4.196	0.014	3.214
ΔOCL	0.008	6.630	0.013	2.923

Notes: This table provides means and coefficients of variation (CV) of selected working capital accounts, earnings, accruals, and cash flows relative to average total assets for the U.S. food supply chain for the 1970–2004 period. The sample contains only domestic agribusinesses traded on the NYSE, AMEX, and NASDAQ stock exchanges, and with available data for the variables defined in this study in both CRSP and Compustat databases (8,553 agribusiness-year observations). "All the U.S. Market" represents the complete U.S. market (with the exception of financial firms) reported by Chan et al. (2006, Table 1, p. 1050). The Chan et al. study includes all firms listed on the NYSE, AMEX, and NASDAQ stock exchanges from 1971 to 1995 with available data, according to their definition of variables, in both CRSP and Compustat. The sample is restricted to domestic, primary stocks.

[a] Panel A provides operating working capital components: current assets is Compustat item 4; current liabilities, item 5; accounts receivable, item 2; inventories, item 3; and accounts payable, item 70.

[b] Panel B reports statistics on earnings and its accruals and cash flow components. Accruals are estimated under the balance sheet approach as the change in noncash current assets minus the change in current liabilities excluding debt and taxes payable and minus depreciation and amortization [text equations (6) and (7)]. Earnings is operating income after depreciation (item 178), and cash flow is earnings minus accruals.

[c] Panel C provides accruals decomposed as in text equations (6) and (7). All variables in the table are divided by average total assets, the average of beginning and ending book value total assets (Compustat item 6).

Panel B of Table 1 provides statistics on earnings and its balance sheet accrual and cash flow components. On average, the food supply chain yields 270 basis points less earnings relative to average total assets than the U.S. market (0.094 compared to 0.121). The difference on reported earnings is primarily due to a lower level of accruals (−0.044 compared to −0.012) rather than to differences on cash flows. For a given level of reported earnings, the food supply chain generates more cash flows than the average U.S. firm.

Accruals decomposed according to equations (6) and (7) are presented in Panel C of Table 1. Depreciation and amortization (*DA*) is the largest component of accruals, but it has the lowest variability as given by the coefficient of variation. For equation (7), as one would expect, the main components of accruals excluding depreciation and amortization are the components of the operating working capital—namely, change in accounts receivable (ΔAR), change in inventories (ΔINV), and change in accounts payable (ΔAP). These three components generate a net operating working capital ($\Delta AR + \Delta INV - \Delta AP$) of 0.014 for the food supply chain compared to 0.042 for the market. This 0.028 difference of net operating working capital as a percentage of total assets could be of economic importance since it signifies, for the food supply chain, cash that does not need to be tied to operations compared to the average U.S. firm and represents almost one-third of average reported earnings.

To obtain a better picture of how accruals and its components vary across firms and what the relationships are among variables, results for the food supply chain are sorted and presented by portfolios of accruals. Following the literature, every year all agribusinesses in the sample are ranked according to the size of accruals and assigned to one of 10 equal sized portfolios. Mean and median of earnings, accruals, and cash flow along with size proxies by portfolio for the food supply chain over the 35-year period of study are provided (Table 2). Portfolio 1 in the table contains agribusinesses with the lowest level of accruals, portfolio 2 contains agribusinesses with the second lowest level of accruals, up to portfolio 10, which contains agribusinesses with the highest level of accruals.

Panel A in Table 2 reports earnings (*Ear*) and its two components, accrual (*Acc*) and cash flow (*CF*). There is a negative relationship between accruals and cash flow across portfolios. As one moves from portfolio 1 with –0.194 mean and –0.163 median for accruals to portfolio 10 with a mean of 0.117 and median of 0.085, cash flows decrease from 0.199 mean and 0.218 median in portfolio 1 to –0.034 mean and 0.004 median for portfolio 10. With the exception of the mean of cash flow for portfolio 3, all cash flow values decrease monotonically across portfolios. In contrast, earnings increase as do accruals, from a mean of 0.005 and median of 0.043 in portfolio 1 to a mean of 0.084 and median of 0.099 in portfolio 10. With the exception of portfolio 10, average earnings increase monotonically across portfolios as accruals increase. Agribusinesses in portfolio 1 report low earnings (0.005 mean and 0.043 median) and very high cash flows (0.199 mean and 0.218 median) while agribusinesses in portfolio 10 report earnings with a mean of 0.084 (around the overall average earnings for the food supply chain of 0.094 reported in Table 1), but generate negative cash flow, very different from the average cash flow generated for the food supply chain (0.139 in Table 1). This finding highlights the need to study reported earnings for the food sector disaggregating firms by accruals.

Panel B of Table 2 presents potential size control variables that are commonly used as risk proxies. One size proxy is market capitalization (*Cap*), which is defined as the natural logarithm of market capitalization, the stock price as of four months following the end of fiscal year multiplied by its contemporaneous number of shares outstanding, both variables as given by CRSP. Consistent with previous studies, market capitalization across portfolios follows an inverted U-shape. Portfolios in the extremes contain the smallest firms across portfolios (mean and median of 3.108 and 2.860 for portfolio 1, and 3.770 and 3.567, respectively, for portfolio 10). The natural logarithm of sales is also used to proxy size. Results on sales are consistent with results on market capitalization across portfolios.

The properties of earnings and its components were first shown in decile portfolios by Sloan (1996) for the complete U.S. market. This approach has been replicated in the same format by Chan et al. (2006) and by Kothari, Loutskina, and Nikolaev (2006).

Table 2. Components of Earnings and Risk Proxies by Decile Portfolios for the U.S. Food Supply Chain

Variable		Port 1	Port 2	Port 3	Port 4	Port 5
PANEL A. Earnings and Its Two Components[a]						
Acc	Mean	−0.194	−0.108	−0.083	−0.067	−0.054
	Median	−0.163	−0.108	−0.086	−0.071	−0.058
CF	Mean	0.199	0.181	0.189	0.174	0.161
	Median	0.218	0.192	0.187	0.172	0.161
Ear	Mean	0.005	0.074	0.106	0.107	0.107
	Median	0.043	0.087	0.103	0.104	0.109
PANEL B. Size Proxies[b]						
Cap	Mean	3.108	3.774	4.277	4.490	4.805
	Median	2.860	3.567	4.121	4.396	4.552
Sales	Mean	4.449	5.045	5.474	5.657	5.976
	Median	4.369	5.113	5.446	5.642	6.016

Notes: This table reports earnings (*Ear*), accruals (*Acc*), and cash flows (*CF*) along with risk proxies by accrual decile portfolios for the U.S. food supply chain for the 1970–2004 period. The sample comprises 8,553 agribusiness-year observations. Portfolios are formed by ranking agribusinesses on the magnitude of balance sheet accruals. Every year agribusinesses in the sample are ranked according to accruals and assigned to one of 10 equal sized portfolios. Mean and median by portfolio are reported for the sample over the 35-year period of study. Portfolio 1 contains agribusinesses with the lowest level of accruals, portfolio 2 contains agribusinesses with the second lowest level of accruals, up to portfolio 10, which contains agribusinesses with the highest level of accruals.

[a] Panel A provides earnings (*Ear*) and its two components, accruals (*Acc*) and cash flow (*CF*). Earnings is operating income after depreciation (Compustat item 178) divided by average total assets (item 6), and cash flow is earnings minus accruals. Accruals is defined as in text equation (7). All variables in equation (7) are divided by average total assets, the average of beginning and ending book value total assets (Compustat item 6).

[b] Panel B provides size control variables commonly used as risk proxies. The first size proxy is market capitalization (*Cap*), which is the natural logarithm of market capitalization, the stock price as of four months following the end of the fiscal year multiplied by its contemporaneous number of shares outstanding, both variables as given by CRSP. Market capitalization is aligned to the beginning of year $t + 1$ return cumulation, following year t portfolio formation. This ensures we are analyzing the properties of the portfolios that will be related to (future) $t + 1$ returns. The second size proxy in Panel B is *Sales*, the natural logarithm of sales (Compustat item 12), which also is frequently used to proxy size.

[table extended → . . .]

Results for the food supply chain in Table 2 are similar to those reported by previous studies for the U.S. market. These simple properties of earnings and its components form the basis for the hypothesis formulated by Sloan (1996) that earnings attributable to the accrual component of earnings are less persistent into the future than earnings attributable to the cash flow performance of earnings. With further development, this generates Sloan's so-called fixation hypothesis, which states that investors are earnings-oriented and do not recognize the information on accruals when implementing their trading strategies. The fixation hypothesis then predicts that realized returns are systematically different from expected returns (i.e., expectations fixated on earnings), and opens the possibility for arbitrage.

Properties of accruals across portfolios are further examined in Table 3. Mean and median for components of accruals are presented by decile portfolios formed by ranking firms according to level of balance sheet accruals as before. The change in noncash current assets ($\Delta NCCA$) increases monotonically across portfolios as accruals increase.[14] In contrast, the changes in

[14] Recall that firms are sorted by accrual rather than by $\Delta NCCA$, which is the first row in the table and might cause confusion. Accruals are not tabulated.

Table 2. Extended

Variable		Port 6	Port 7	Port 8	Port 9	Port 10
PANEL A. Earnings and Its Two Components [a]						
Acc	Mean	−0.042	−0.027	−0.009	0.017	0.117
	Median	−0.046	−0.032	−0.014	0.013	0.085
CF	Mean	0.154	0.140	0.126	0.100	−0.034
	Median	0.154	0.140	0.125	0.098	0.004
Ear	Mean	0.112	0.113	0.116	0.117	0.084
	Median	0.114	0.112	0.118	0.115	0.099
PANEL B. Size Proxies [b]						
Cap	Mean	5.003	5.009	4.976	4.730	3.770
	Median	4.898	4.783	4.870	4.518	3.567
Sales	Mean	6.114	6.167	5.902	5.646	4.862
	Median	6.168	6.160	5.983	5.645	4.950

current liabilities excluding debt and taxes payable ($\Delta NCCL$) decrease. Depreciation and amortization (DA) decreases across portfolios as well, but the variation from portfolio to portfolio is low. In addition, DA is more stable across portfolios, as means and medians are very similar. Change in accounts receivable (ΔAR) and change in inventories (ΔINV) have similar magnitudes and increase monotonically, while ΔAP varies little across portfolios.

The magnitudes of $\Delta NCCA$ and $\Delta NCCL$ across portfolios are notably different, with the exception of portfolio 5. In this portfolio, average $\Delta NCCA$ and $\Delta NCCL$ both equal 0.015, with respective medians of 0.012 and 0.013. These magnitudes net to zero [in equation (6)], and accruals is simply negative depreciation and amortization (the −0.054 mean reported in Table 2). This implies that earnings before interest, taxes, depreciation, and amortization, commonly known as EBITDA (operating earnings plus depreciation and amortization), equals cash flow for this portfolio. This result of portfolio 5 in the middle of the spectrum of agribusinesses is, as expected, close to average results of the complete sample for the food supply chain [average EBITDA for the food supply chain, operating earnings (0.094) plus depreciation and amortization (0.053), equals 0.147 compared to 0.139 cash flow in Table 1]. Thus, on average, EBITDA and cash flow are *apparently* similar for the food supply chain. Given the importance of EBITDA, this metric and its validity as a proxy for cash flow is further examined.

EBITDA as a Proxy for Cash Flow

Shin and Soenen (1998) and Lakonishok, Shleifer, and Vishny (1994), among others, use EBITDA to proxy cash flow. Although the research questions in those studies are not related to accruals, this raises the empirical question of whether EBITDA could be a valid proxy for cash flow in accrual research studies.

Companies disclose numerous earnings performance measures, including EBITDA, in addition to those defined by the generally accepted accounting principles (Moehrle, Reynolds-Moehrle, and Wallace, 2003). Furthermore, EBITDA has been widely adopted as a proxy for cash flows of operations (Shook, 2003; Strum, 2003), and users have apparently overlooked its limitations (Stumpp, 2000). In the extreme, "some within the lending and investment worlds have attempted to merge the EBITDA concept into the FCF [free cash flow] concept by subtracting 'maintenance CAPEX' from EBITDA.

Table 3. Components of Accruals by Decile Portfolios for the U.S. Food Supply Chain

Variable		Port 1	Port 2	Port 3	Port 4	Port 5
$\Delta NCCA$	Mean	−0.079	−0.011	0.005	0.009	0.015
	Median	−0.042	−0.003	0.005	0.008	0.012
$\Delta NCCL$	Mean	0.046	0.029	0.024	0.016	0.015
	Median	0.033	0.027	0.020	0.015	0.013
DA	Mean	0.068	0.068	0.064	0.060	0.054
	Median	0.063	0.066	0.064	0.059	0.054
ΔAR	Mean	−0.032	−0.003	0.002	0.002	0.005
	Median	−0.009	0.000	0.001	0.002	0.004
ΔINV	Mean	−0.035	−0.006	0.003	0.005	0.008
	Median	−0.005	0.001	0.002	0.003	0.004
ΔOCA	Mean	−0.012	−0.002	−0.000	0.002	0.002
	Median	−0.001	0.000	0.001	0.001	0.001
ΔAP	Mean	0.019	0.015	0.015	0.009	0.009
	Median	0.011	0.011	0.009	0.007	0.006
ΔOCL	Mean	0.028	0.014	0.010	0.007	0.006
	Median	0.013	0.010	0.009	0.006	0.005

Notes: This table reports components of accruals by accrual decile portfolios for the U.S. food supply chain for the 1970–2004 period. The sample comprises 8,553 agribusiness-year observations. Portfolios are formed by ranking agribusinesses on the magnitude of balance sheet accruals. Every year agribusinesses in the sample are ranked according to accruals and assigned to one of 10 equal sized portfolios. The table provides mean and median of the components of accruals (accruals are not shown to avoid repetition) by portfolio for the sample over the 35-year period of study. Portfolio 1 contains agribusinesses with the lowest level of accruals, portfolio 2 contains agribusinesses with the second lowest level of accruals, up to portfolio 10, which contains agribusinesses with the highest level of accruals. Components of accruals are given according to text equations (6) and (7). All variables in both equations are divided by average total assets, the average of beginning and ending book value total assets (Compustat item 6).

[table extended ➤ . . .]

Subtracting total CAPEX expenditures from EBITDA and calling it FCF is common" (Zoeller, 2002, p. 36).

Academics and practitioners have serious doubts about the use of EBITDA as a proxy for cash flow, arguing that EBITDA is often misleading. One of the most referenced publications on EBITDA is the special comment released by Moody's (Stumpp, 2000), in which the main failures of EBITDA are presented using case studies. There is, however, a lack of empirical results on EBITDA.

As highlighted in the previous section, EBITDA for the food supply chain equals cash flow only for firms in decile portfolio 5 formed by ranking agribusinesses on level of accruals. EBITDA and cash flow are also similar on average for all agribusinesses in the sample. This finding highlights the concern regarding the use of EBITDA as a proxy for cash flow, since it means that on average changes in net operating working capital equal zero (i.e., working capital management does not matter).

We find it necessary to redefine the measurement of variables to test the variation of EBITDA across the spectrum of agribusinesses ranked by accruals. Under our empirical design, the relationship between EBITDA and cash flow would unambiguously be negative since the only component added to operating earnings to calculate EBITDA is depreciation and amortization, which is positive. This follows from the fact that the relationship between accruals and cash flow has been shown to be negative across portfolios, and the relationship between accruals and earnings is positive.

Table 3. Extended

Variable		Port 6	Port 7	Port 8	Port 9	Port 10
ΔNCCA	Mean	0.024	0.031	0.046	0.070	0.164
	Median	0.019	0.027	0.040	0.064	0.137
ΔNCCL	Mean	0.014	0.012	0.014	0.013	0.011
	Median	0.010	0.010	0.010	0.011	0.019
DA	Mean	0.052	0.046	0.042	0.040	0.035
	Median	0.051	0.046	0.040	0.037	0.033
ΔAR	Mean	0.009	0.010	0.018	0.026	0.063
	Median	0.006	0.008	0.014	0.020	0.042
ΔINV	Mean	0.012	0.016	0.025	0.036	0.084
	Median	0.007	0.012	0.017	0.030	0.068
ΔOCA	Mean	0.002	0.004	0.004	0.008	0.018
	Median	0.001	0.002	0.002	0.003	0.004
ΔAP	Mean	0.008	0.007	0.008	0.008	0.017
	Median	0.005	0.005	0.006	0.006	0.012
ΔOCL	Mean	0.005	0.005	0.006	0.005	–0.005
	Median	0.005	0.004	0.004	0.005	0.005

Thus, instead of using operating earnings to test EBITDA, we measure earnings as earnings before extraordinary items and discontinued operations. Also, since the concern is to examine the relationship between cash flow and a potential proxy, *actual* cash flow from operations is taken directly from the statement of cash flow rather than *estimated* indirectly through balance sheet accruals. Equation (8) is used for this test. Accruals are calculated as the difference between earnings (Compustat item 123) and cash flows (cash flow from operations, item 308, plus extraordinary items and discontinued operations, item 124).

The use of data from the statement of cash flow reduces the sample from 8,553 to 4,071 firm-year observations with available data to compute accruals (Acc_{CF}). Table 4 reports mean values of portfolios formed as before but by quintiles instead of deciles to compensate for the reduction of the sample. With the exception of the portfolio with the lowest accruals, accruals (Acc_{CF}) and cash flow (*CFO*) are negatively related across portfolios. EBITDA, however, is not negatively related to accruals. Rather, it increases as one moves from portfolio 1 to portfolio 3 and only slightly decreases thereafter. The final row of Table 4 shows the difference between EBITDA and cash flow. The mean values for EBITDA are higher than those for cash flow under portfolios 2–5. An agribusiness reporting a mean of 0.037 accruals in portfolio 5 would have a very low cash flow from operations (0.010), but will be reporting a high EBITDA of 0.127. Only agribusinesses with the lowest level of accruals have average EBITDA similar to *CFO*. Both the magnitude and the pattern of EBITDA across different levels of cash flows for agribusinesses are misleading since they do not mimic cash flows.

The discussion so far pertains to the relationship among fundamentals. We include stock returns in our analysis to examine the relationships between fundamentals and market data. Buy-and-hold returns inclusive of dividends one year ahead of portfolio formation (*Returns* $t + 1$ in Table 4) reveal that as firms report lower levels of cash flow, their stock returns deteriorate in the following period. At the extreme, firms in portfolio 5 that report 1% of cash flow relative to total assets, report 4.7% of earnings before extraordinary items and discontinued operations but they still report a high level

Table 4. Earnings Before Interest, Taxes, Depreciation, and Amortization (EBITDA), Earnings and Its Components, and Future Returns by Quintile Portfolio for the U.S. Food Supply Chain

Variable	Port 1	Port 2	Port 3	Port 4	Port 5
Acc_{CF}	-0.220	-0.091	-0.061	-0.033	0.037
CFO	0.088	0.118	0.108	0.082	0.010
EBXI	-0.132	0.028	0.046	0.049	0.047
EBITDA	0.069	0.153	0.161	0.150	0.127
Returns $t+1$	0.122	0.120	0.114	0.109	0.083
EBITDA – CFO	-0.019	0.034	0.053	0.067	0.116

Notes: This table provides earnings and its two components (accruals and cash flows), EBITDA for current year t, and buy-and-hold annual returns for $t+1$ by accrual quintile portfolios for the U.S. food supply chain for the 1970–2004 period, and with available data in both CRSP and Compustat databases to calculate accruals under the statement of cash flow approach. The subset sample contains 4,071 firm-year observations. Portfolios are formed by ranking agribusinesses on the magnitude of statement of cash flow accruals [text equation (8)]. Every year agribusinesses in the sample are ranked according to accruals and assigned to one of five equal sized portfolios. Table 4 reports average of selected variables as described below for the sample over the 35-year period of study. Portfolio 1 contains agribusinesses with the lowest level of accruals, portfolio 2 contains agribusinesses with the second lowest level of accruals, up to portfolio 5, which contains agribusinesses with the highest level of accruals. Earnings (*EBXI*) is earnings before extraordinary items and discontinued operations (Compustat item 123), cash flow (*CFO*) is cash flow from operations as given in the statement of cash flows (item 308) minus extraordinary items and discontinued operations (item 124). All items are divided by total assets (item 6). Accruals (Acc_{CF}) is the difference between *EBXI* and *CFO*. *EBITDA* is operating income after depreciation (item 178) plus depreciation and amortization (item 14), all divided by total assets (item 6). Stock buy-and-hold returns in year $t+1$ (*Returns* $t+1$) are calculated as

$$BHR_{i,t} = \prod_{j=1}^{12} (1 + r_{i,j}) - 1,$$

where $BHR_{i,t}$ is the buy-and-hold compound annual return for firm i in year t, and $r_{i,j}$ is CRSP monthly rate of return inclusive of dividends and all other distributions over month j. Year refers to fiscal year as defined in Compustat. The return cumulation period starts four months after the end of the agribusiness' fiscal year. Thus, returns reported in this table are $t+1$ returns following financial statements reported (all other variables in the table) in t.

of EBITDA (12.7%). Agribusinesses in the portfolio with the highest accruals have, on average, low future stock returns (i.e., 8.3% for portfolio 5), which is most probably a negative abnormal return. These results support the appeal of EBITDA to managers when providing performance measures to stakeholders, and emphasize the economic misleading nature of EBITDA.

Conclusions

This paper examines empirical relationships of earnings, accruals, and cash flows for the food supply chain sector (i.e., agribusiness). In addition, EBITDA is evaluated as a potential proxy for cash flow.

While earnings and accruals are systematically positively related, accruals and cash flows are systematically negatively related. Agribusinesses monotonically decrease cash flow as they increase their accruals and accounting earnings. This result for the food supply chain, which represents around 8% of the complete U.S. market in terms of number of firms, is consistent with previous studies covering the complete U.S. market [initially documented by Dechow (1994) and Sloan (1996)]. In those studies it is emphasized that results vary across industries, depending on the industries' structures of working capital.

Documenting those empirical relationships in the food sector is important for the following reasons. First, in previous studies on accruals for the entire U.S. market, either no specific industry results are provided or the definition of industries is broad. Thus, it is not possible to characterize the food supply chain sector with regard to accruals from previous empirical work.

Second, these simple properties of earnings and its components form the basis for the hypothesis formulated by Sloan (1996) that earnings attributable to the accrual component of earnings are less persistent into the future than earnings attributable to the cash flow performance of earnings. With further development, this generates the so-called fixation hypothesis or accruals anomaly, which states that investors are too current-oriented or naively fixated toward earnings and do not fully recognize the information in accruals and cash flows, and are consequently fooled by managers manipulating earnings (i.e., earnings management).

Alternative potential explanations to earnings management for the accruals anomaly are currently under debate in the financial accounting economics literature. A well-articulated hypothesis on the accrual anomaly has not yet been offered. The fact that the empirical relationships of accruals, earnings, and cash flows for the food sector behave similarly to results for the complete U.S. market constitutes a first step for further research in this important area, in particular for agribusiness. [Sloan's 1996 work has been referred to as a "landmark paper" (Strum, 2003), and his documented accrual anomaly as a "startling finding" (Thomas and Zhang, 2002) and an "intriguing" result (Chan et al., 2006).]

In addition, this paper contributes by analyzing EBITDA as a proxy for cash flow under the accrual model. It is shown that EBITDA might be misleading as a metric intended to convey financial performance information and should not be used as a proxy for cash flow of operations. As a by-product of this research, the test of EBITDA calls for the use of statement of cash flow accruals as opposed to balance sheet accruals. Thus, the relationships of accruals, earnings, and cash flows are shown to be consistent when measured under alternative approaches.

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Appendix Table A1. Selected Financial Statements Items

Item Name	Compustat Item Number
Cash and short-term investments	1
Receivables	2
Inventories	3
Other current assets	68
Current assets—Total (1 + 2 + 3 + 68)	4
Assets—Total	6
Debt in current liabilities	34
Accounts payable	70
Income taxes payable	71
Other current liabilities	72
Current liabilities—Total (34 + 70 + 71 + 72)	5
Liabilities—Total	181
Stockholders' equity—Total	216
Sales	12
Cost of goods sold	41
Selling, general, and administrative (SG&A) expenses	189
Depreciation & amortization	14
Operating income after depreciation and amortization	178
Interest expenses	15
Nonoperating income (expense)	61
Special items	17
Income taxes	16
Income before extraordinary items	18
Extraordinary items, discontinued operations, and other	48 + 191
Net income (loss)	172
Income before extraordinary items	123
Depreciation & amortization	125
Extraordinary items and discontinued operations	124
Other adjustments to income	126 + 106 + 213 + 217
Decrease (increase) in accounts receivable	302
Decrease (increase) in inventories	303
Increase (decrease) in accounts payable	304
Increase (decrease) in income taxes	305
Net change in other assets and liabilities	307
Cash flow from operation activities (123 + 125 + 124 + 126 + 106 + 213 + 217 + 302 + 303 + 304 + 305 + 307)	308
Cash flow from investment activities	311
Cash flow from financing activities	313
Cash and cash equivalents—Increase (Decrease)	274

Notes: This table presents compact balance sheet, income statement, and statement of cash flow with selected items. The level of disaggregation is provided according to the needs in this study.

Appendix Table A2. Distribution of Agribusinesses by Year and Industry

Industry	1970	1971	1972	1973	1974	1975	1976	1977	1978	1979
Bakery	5	6	7	9	9	10	8	8	9	9
Beverages	17	20	21	30	37	37	36	34	32	30
C, F, and PF & V[a]	12	11	12	17	19	18	19	19	17	16
Dairy	7	7	7	12	12	12	12	10	9	9
Fats & oils	1	1	1	3	4	4	4	3	3	2
Grain milling	14	18	18	20	23	23	21	22	20	20
Meat	13	13	13	20	29	29	30	29	26	25
Miscellaneous food & kindred	3	3	4	7	10	10	10	10	11	9
Sugar & confectionery	11	11	11	13	14	14	14	13	12	13
Tobacco	11	12	12	13	13	11	11	10	10	10
Total Food Processing & Beverage	94	102	106	144	170	168	165	158	149	143
Food service	10	15	16	38	53	60	58	58	56	53
Food stores—Retail	34	36	37	57	63	66	64	60	57	54
Grocery & related prods.—Wholesale	4	5	10	18	23	24	25	25	22	19
Total Food Wholesale, Retail & Service	48	56	63	113	139	150	147	143	135	126
Grand Total Food Supply Chain	142	158	169	257	309	318	312	301	284	269

Industry	1988	1989	1990	1991	1992	1993	1994	1995	1996	1997
Bakery	5	6	5	5	5	5	5	8	9	7
Beverages	21	20	20	18	18	16	20	21	27	29
C, F, and PF & V[a]	14	13	13	13	14	15	13	17	17	17
Dairy	12	12	11	10	12	14	13	12	10	9
Fats & oils	—	—	—	—	—	—	—	1	1	1
Grain milling	14	14	14	14	14	12	11	12	12	12
Meat	24	24	25	25	25	25	25	23	20	16
Miscellaneous food & kindred	11	10	11	9	10	9	14	12	12	12
Sugar & confectionery	10	10	9	9	8	9	9	10	10	10
Tobacco	4	4	4	4	3	3	3	4	4	3
Total Food Processing & Beverage	115	113	112	107	109	108	113	120	122	116
Food service	73	63	69	71	73	90	96	106	113	107
Food stores—Retail	30	29	31	29	30	37	36	37	38	35
Grocery & related prods.—Wholesale	22	20	21	19	16	16	25	26	23	22
Total Food Wholesale, Retail & Service	125	112	121	119	119	143	157	169	174	164
Grand Total Food Supply Chain	240	225	233	226	228	251	270	289	296	280

Notes: This table presents the U.S. food supply chain for the 1970–2004 period (number of agribusinesses per year). The sample contains only domestic agribusinesses traded on the NYSE, AMEX, and NASDAQ stock exchanges, and with available data for the variables defined in this study in both CRSP and Compustat databases. Three-digit SIC code industries are separated into two major industry groups: (1) food processing and beverage, and (2) food wholesale, retail, and service. SIC group classifications are as follows: bakery (SIC 205); beverages (208); canned, frozen, and preserved fruits & vegetables (203); dairy (202); fats and oils (207); grain milling (204); meat (201); miscellaneous food preparations & kindred (209), which also includes other "food & kindred product" firms not elsewhere classified; sugar and confectionery (206); tobacco (21); food service (5810 and 5812); retailers (5400 and 5411); and wholesalers (5140, 5141, and 5180).

[a] C, F, and PF & V denotes canned, frozen, and preserved fruits & vegetables.

[table extended ‣ . . .]

Appendix Table A2. Extended

Industry	1980	1981	1982	1983	1984	1985	1986	1987	1970–1987
Bakery	7	6	5	5	5	6	4	5	123
Beverages	26	24	20	22	19	18	21	21	465
C, F, and PF & V[a]	16	15	15	14	15	11	13	14	273
Dairy	7	8	6	6	6	6	7	9	152
Fats & oils	1	1	1	2	2	2	—	—	35
Grain milling	22	23	21	21	18	17	15	15	351
Meat	22	20	21	20	18	17	18	17	380
Miscellaneous food & kindred	9	8	7	8	8	6	5	9	137
Sugar & confectionery	14	14	11	11	9	9	11	9	214
Tobacco	10	9	8	7	7	5	5	5	169
Total Food Processing & Beverage	134	128	115	116	107	97	99	104	2,299
Food service	55	53	58	61	78	82	79	82	965
Food stores—Retail	54	53	50	48	52	52	40	34	911
Grocery & related prods.—Wholesale	20	19	20	19	17	17	18	19	324
Total Food Wholesale, Retail & Service	129	125	128	128	147	151	137	135	2,200
Grand Total Food Supply Chain	263	253	243	244	254	248	236	239	4,499

Industry	1998	1999	2000	2001	2002	2003	2004	1988-2004	1970-2004
Bakery	7	9	4	4	5	4	4	97	220
Beverages	28	28	26	23	23	22	19	379	844
C, F, and PF & V[a]	18	17	17	12	11	11	10	242	515
Dairy	10	13	12	10	8	6	6	180	332
Fats & oils	1	3	3	5	5	5	5	30	65
Grain milling	10	12	11	7	7	6	4	186	537
Meat	17	15	15	11	11	11	11	323	703
Miscellaneous food & kindred	12	10	11	12	14	13	11	193	330
Sugar & confectionery	10	10	8	9	9	9	9	158	372
Tobacco	4	2	3	4	4	4	4	61	230
Total Food Processing & Beverage	117	119	110	97	97	91	83	1,849	4,148
Food service	100	96	82	71	69	65	58	1,402	2,367
Food stores—Retail	31	26	25	23	20	20	17	494	1,405
Grocery & related prods.—Wholesale	20	19	14	13	12	11	10	309	633
Total Food Wholesale, Retail & Service	151	141	121	107	101	96	85	2,205	4,405
Grand Total Food Supply Chain	268	260	231	204	198	187	168	4,054	8,553

Financing Strategies Under Combined Capital Structure Theories: A Farm-Level Simulation Analysis

Jianmei Zhao, Peter J. Barry, and Gary D. Schnitkey

Abstract

A stochastic, multi-period simulation model is developed based on the prevalent capital structure theories, in searching for and identifying an optimal combination of related financing strategies. The model reflects both conceptual and empirical implications of the pecking order, trade-off, and signaling theories on farm business financing, investment, and expansion process. The comparisons of simulation output indicate that farm businesses could expand at a moderate speed accompanied by financial health when they concurrently adopt these financing tactics. Pecking order financing benefits short-term financial management, trade-off strategy effectively adjusts farm capital structure, and the signaling theory enables the adoption of risk-adjusted interest rate policies between the farm borrower and the lender.

Key words: pecking order, signaling theory, simulation, trade-off

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According to the Illinois Farm Business Farm Management (FBFM) Association, large-scale farms of several thousand acres are in the vanguard of Midwestern crop farming in the United States. The operators of these farms lease most (e.g., 80% to 90%) of the land, with a combination of cash and share leases. Market, financial, environmental, and other types of risks must be continually monitored and managed. Family partnerships are common in these large operations, with varying amounts of seasonal and full-time labor. Still, for these commercial-scale farms, expansion in size remains a high priority in order to realize scale economies, increase income, build equity capital, and achieve other financial goals. Access to financial capital is crucial, based on effective financial planning and dependable business relationships. The informational needs and planning processes go well beyond traditional credit risk assessment, reflecting a mutual understanding by farmers and lenders of investment dynamics, financial behavior, and alternative approaches to managing farm capital structure.

Previous studies in corporate and agricultural finance have shown that the trade-off, pecking order, and signaling theories can jointly and significantly affect a firm's capital structure (Barry, Bierlen, and Sotomayor, 2000; Zhao, Barry, and Katchova, 2008). The trade-off theory reflects a long-run adjustment process toward an optimal relationship between a firm's debt and equity capital. The pecking order effect implies a preference for the use of internal funds over external funds in meeting the operating costs and other short-term obligations. Signaling theory rests upon a lender responding with lower interest rates, expanded credit capacity, or both, to borrowers who can send credible signals of lower credit risk. Taken together, the three theories combine a borrower's capital structure decisions with a lender's determination of the cost and availability of credit in the creation of credit relationships and the resulting credit effects on business performance.

Related studies in agricultural finance have considered how capital structure is influenced by business and demographic characteristics, as well as public policies (Featherstone et al., 2005). Included are farmers' risks and risk attitudes, the time period and general economic conditions, tax policies, business versus financial risks, and dynamic versus static analyses (Ahrendsen, Collender, and Dixon, 1994; Escalante and Barry, 2003; Jensen and Langemeier, 1996; Gwinn, Barry, and Ellinger, 1992; Collins and Karp, 1995).

Applicable to the present study are recent emphases on financial market imperfections and the use of external versus internal sources of funds (Hubbard and Kashyap, 1992; Bierlen and Featherstone, 1998; Jensen, Lawson, and Langemeier, 1993). Barry, Bierlen, and Sotomayor (2000) tested the joint effects of the partial adjustment and pecking order theories on farm businesses; Zhao, Barry, and Katchova (2008) extended this work by adding the signaling theory and refining the joint empirical tests of the three capital structure theories. They concluded that farms adjust toward optimal capital structures over time while favoring internal funds in the short run and building credit capacities through signals of improved profitability and cash flow.

These findings of empirical linkages among the capital structure theories suggest that they should be accommodated in planning or projection models for simulating financing strategies for future business performance. The objectives of this study are to design and apply a stochastic, multi-period simulation model that captures farm businesses' expansion and directly represents these capital structure theories, in searching for and identifying an optimal combination of related financing strategies. The model will reflect both conceptual and empirically based specifications for an Illinois cash grain farmer's investment decisions, financing strategies, land tenure, risk and liquidity positions, as well as the lender's use of risk-adjusted interest rates in response to signals of low versus high credit risk. Alternative scenarios will distinguish among the separate and combined effects of different financing and lending policies on growth in net equity, default rate, and risk ratings.

Review of Capital Structure Theories

Currently prevalent capital structure theories effectively describe the financing strategies employed by corporate firms. The pecking order theory of capital structure, originally developed by Myers (1984) and Myers and Majluf (1984), states that firms use internal funds first because they are less costly than external funds. When external funds are used, the sequence is debt followed by equity, reflecting the ordering of financing costs, although external equity is seldom used. These ideas were formulated into testable hypotheses and confirmed by many studies, including Baskin (1989); Jensen, Solberg, and Zorn (1992); and Hubbard (1998).

The trade-off theory predicts a target debt-to-asset ratio that depends on the costs and benefits of financial leverage. Benefits of higher leverage include the tax deductibility of interest paid and the use of debt to indicate high quality performance induced by managerial efforts to meet the financial obligations. Costs of higher leverage include the greater likelihood of liquidation and its associated costs, and agency costs due to borrowers' incentives to take actions that might be detrimental to lenders. If adjustment to a changing target is costly due to market imperfections, the theory implies that a partial adjustment model is appropriate. The optimal debt target is not observed directly and likely varies over time. Early tests of target models include Taggart (1977) and Jalilvand and Harris (1984). Hovakimian, Opler, and Titman (2001) conducted a more extensive search for the evidence of target-adjustment financing; they found that management acts to move the firm toward a target debt ratio, and that the target depends on characteristics of the firm.

Signaling theory applied to finance was developed by several studies, including Spence (1973), Ross (1977), and Diamond (1989). A credible signal can distinguish a high-quality firm from a low-quality firm, if the latter is unable to mimic the signal or finds it too costly to do so. Empirical applications of signaling in the lender-borrower relationship are scarce. One empirical application is provided by Shenoy and Koch (1996), who confirmed the pecking order financing and the signaling effect do exist in the borrower-lender relationship.

In agricultural capital markets, asymmetric information prevents lenders from completely distinguishing financial health among diverse farm borrowers. While lenders tend to require similar types of information from borrowers, the quality, completeness, and extent of documentation they provide may vary widely. Thus, good quality borrowers have incentives to convey their advantageous credit risk information to lenders through credible signals. Especially important is the information about key financial factors, such as profitability, repayment capacity, solvency, and liquidity. Meanwhile, effective use of risk management practices, marketing alternatives, and educational programs are other signaling examples (Miller et al., 1993).

Empirical Simulation of Capital Structure Theories

One goal of the model design is to represent the capital structure theories in conceptually sound, yet empirically practical ways for farm businesses. "Conceptually sound" means: (*a*) the trade-off theory allows different rates of adjustment toward target levels of the debt-to-asset ratio; (*b*) the pecking order theory relies on internal funds to meet operating costs in the short term; and (*c*) credible signaling elicits lower, risk-adjusted interest rates from lenders. The practical dimension means that the model must rely on key assumptions and decision rules to implement the respective theories. In several cases, benchmark ratios are established to represent structural targets for the simulated farm and to allow acreage expansion, investments, and additional financing until the structural benchmarks are reached.

Trade-off Specifications

The spirit of the trade-off theory is that farms pursue an optimal debt-to-asset ratio which balances the advantages (tax deductibility of interest) against the disadvantages (financial stress and agency costs) of the debt capital. A farm employing the trade-off strategy monitors its debt-to-asset ratio, adjusting it to target levels through capital investments and the related financing transactions. Questions of when, how, and how much to expand are critical in the simulation design.

Expansion can occur when a farm's debt-to-asset ratio is below its target level as well as farm expansion requirements. In this study, the target debt-to-asset ratio is empirically determined in each year, based on the observed relationship between farm size in acres and the leverage position.[1]

[1] While the target level of leverage is conceptually determined by minimizing the weighted average costs of debt and equity capital, we rely on the acreage relationship as a proxy for the conceptual relationship.

FBFM data indicate that tillable acres and the debt-to-asset ratio have a concave relationship. Specifically, leverage tends to increase with acreage, eventually leveling out and declining. Consistent with this concave relationship, a farm's optimal debt-to-asset ratio (D/A^*) is specified as a quadratic relationship to the level of its tillable acres (*Acre*). Using 2005 FBFM data, the estimated quadratic regression is:

$$(1)\quad D/A^* = 25.78 + 0.00925 \times Acre - 0.00000147 \times Acre^2.$$

Both *Acre* and $Acre^2$ indicate the appropriate signs and are significant with *p*-values less than 0.0001. The first-order condition reveals that the debt-to-asset ratio is maximized when farm size is 3,146 acres, and declines thereafter. In the simulation, the target debt-to-asset ratio for each farm is determined by inserting acreage into equation (1) and solving for D/A^*. For example, D/A^* is 33.6% for a 1,000-acre farm and 40.3% for a 3,146-acre farm.

Under the trade-off model, expansion can occur either by land purchase, leasing, or a combination of both. A sequential evaluation occurs in which 50% of available investment capital[2] is first allocated to potential land purchase, with leasing considered thereafter. A land purchase includes expenditures for required machinery and storage. Leasing includes only the machinery expenditure. In each case, the farm business is required to maintain over time its machinery recovery cost[3] on existing tillable acres.

The optimal land purchase acres are determined by equation (2), with the numerator representing a farm's total liabilities after land purchase. The denominator is the total asset value, including the newly purchased land. Financing arrangements for purchased land, machinery, and storage are a 30% down payment and 70% debt capital. No purchase occurs if funds are not available to meet the down payment. Given values of other variables, the target purchased acres ($Acre\_buy^*$) are empirically calculated by solving equation (2):

$$(2)\quad \left\{ \frac{D_0 + Acre\_buy^* \times (Land\_P + Mach\_P + Bldg\_P) \times 70\%}{A_0 + Acre\_buy^* \times (Land\_P + Mach\_P + Bldg\_P)} \right\} = D/A^*,$$

where D_0 and A_0 are initial total debt level and total asset value; D/A^* is the target debt-to-asset ratio. *Land_P*, *Mach_P*, and *Bldg_P* represent per acre land, machinery, and building price, respectively.[4] $Acre\_buy^*$ is the calculated target acres, *Acre_buy* is the minimal integer unit of 40 acres[5] adjacent to $Acre\_buy^*$ that is to be purchased in adjusting to the farm's optimal capital structure.

The speed of adjustment to the optimal capital structure can differ among farms due to transaction costs, market availability, and the conservatism of the farm borrowers. The model contains a range of adjustment speeds defined by a trade-off ratio (*TORatio*), which equals actual borrowing amounts divided by the capital needed to reach the target D/A^*. The *TORatio* ranges from 0 to 1, with higher values representing a faster

[2] Available investment capital is the net cash income minus scheduled principal, interest, and family consumption payments calculated at the end of each year.

[3] The machinery recovery cost is calculated based on tillable acres due to machinery depreciation. In this study, the straight-line method is employed to estimate machinery and building depreciation. The depreciation value, in each year, is equal to market value minus salvage value, divided by depreciation years. The depreciation years for machinery and buildings are assumed to be 10 and 20 years, respectively. The salvage value is 30% of original market value for machinery and 20% for buildings.

[4] Those prices are used in the simulation for each year. Based on FBFM 2005 data, initial land price is assumed to be $3,500 per acre with an increasing rate of 3% in each following year. Machinery price is $240 per acre, increasing at 2% in later years. Following Barry and Ellinger (1989), the building price is assumed to be 5% of land price, and the building purchase is accompanied with the land purchase.

[5] The actual land transactions and leasing in Illinois are based on a per 40-acre basis; this restriction is applied in the simulation.

adjustment speed. In order to avoid the extreme adjustment behavior, yet clearly reflect the differences in economic effects, the model randomly selects a *TORatio* from the 0.5 to 0.8[6] range for trade-off farms that are endowed with different adjustment speeds. The *TORatio* is zero for farms not following the trade-off theory.

Leasing of farmland reflects its extensive use in Illinois. Leasing conserves liquidity and frees up cash flow compared to ownership and debt. However, leasing also foregoes capital gains and increases tenure risk. The level of leasing depends on the farm's tenure ratio[7] relative to its benchmark ratio. The benchmark ratio is the average tenure ratio for different size (tillable acres) groups of Illinois farms based on FBFM data in 2005, which ranges from 0.24 for farms between 300 and 600 acres to 0.14 for farms greater than 1,200 acres. A tenure ratio that exceeds the benchmark for the respective size class promotes the farm business to expand by leasing more farmland, thus maintaining the observed relationship. The target number of acres to lease ($Acre\_lease^*$) is calculated by solving the tenure equation (3), given the values of the other variables:

$$(3)\quad \left\{ \frac{Own\_acre_0 + Acre\_buy \times TORatio}{Own\_acre_0 + Acre\_buy \times TORatio + Acre\_lease^*} \right\} = Tenu^*,$$

where Own_acre_0 is initially owned farmland; $Acre\_buy \times TORatio$ yields actual purchased acres from land purchase. $Tenu^*$ is the appropriate tenure ratio. $Acre\_lease^*$ is the target leased acres and *Acre_lease* is the rounded leased acres based on the 40-acre integer restriction.

Consistent with the speed of adjustment specifications, the actual leased acreage is found by multiplying the *TORatio* by *Acre_lease* for each farm.

The trade-off case is bounded by two extremes that do not follow the trade-off financing characteristics: debt-seeking (risk-loving) and debt-avoiding (ultra-conservative) farms. They allow comparisons to the pecking order farms and signaling results without considering their debt-to-asset ratio. The debt-seeking farm borrows liberally to expand the business, whereas the debt-avoiding farm refrains from borrowing and primarily depends on internal funds for farm expansion.

The debt-seeking and debt-avoiding farms are distinguished from trade-off farms by the allowable range of the investment ratio (*IR*), which is defined as the percentage of capital allocated to farm expansion and nonfarm investment from total available investment capital. For example, investing $30,000 on farm expansion from $100,000 of available investment capital yields an *IR* of 0.3. A higher *IR* implies the farm business tends to make aggressive investments, while a lower value represents a conservative investment attitude. In the simulation, *IR* is randomly selected from the 0.7 to 1.0 range for debt-seeking farms, 0 to 0.3 for debt-avoiding farms, and 0.3 to 0.7 for trade-off farms at the beginning year, and kept constant over the simulation period.

Debt-seeking and debt-avoiding farms balance neither their capital structure nor their tenure ratio. When investing, they concurrently purchase and lease farmland in a 1:4 relationship. The purchased acres can be calculated from equation (4):

$$(4)\quad Acre\_buy = \left\{ \frac{ExpCap}{(L\_dwpy + M\_dwpy + B\_dwpy) + 4 \times M\_dwpy} \right\},$$

where *ExpCap* is the capital allocated to farm expansion. *Acre_buy* represents

[6] The range from 0.5 to 0.8 is arbitrarily determined. It avoids an unlikely, complete adjustment to the optimal D/A^*, while still allowing substantial movement. Once the *TORatio* is randomly assigned for each farm, it holds constant over the simulation period.

[7] Tenure ratio is farm-owned land acres divided by total acres operated.

purchased land acres for farms that do not follow the trade-off theory. *L_dwpy*, *M_dwpy*, and *B_dwpy* are per acre down payments for land, machinery, and building purchase, respectively. The denominator is per acre down payment for non-trade-off farms.

The investment activities of trade-off farms are restrained by two standards: (*a*) the investment needed to adjust their capital structure, and (*b*) the investment needed for expansion. A trade-off farm makes no investments if its debt-to-asset ratio exceeds its target level. When the capital investment is allowed, the actual investment would be the lower value of the two standards. If, for example, a trade-off farm requires $12,000 investment capital to adjust to its target debt-to-asset ratio, yet farm expansion demands $18,000 capital allocation, the actual investment would be $12,000. In contrast, the investment decision by debt-seeking and debt-avoiding farms is simply regulated by their expansion requirements.

For all farms, land purchase and leasing are based on integer times of 40 acres. The minimum land purchase and leasing are restricted to 40 acres, which is consistent with the actual land transactions in Illinois.

Pecking Order Specifications

The pecking order theory emphasizes that, in the short run, farms prefer to employ the internal funds for their operating costs instead of short-term debt. The pecking order ratio (*PORatio*) is defined as the percentage of short-term financing through internal funds relative to total short-term financing needs. For our purposes, a *PORatio* in the range of 0.7 to 1.0 implies a pecking order farm. This farm would utilize more than 70% of its internal capital for the operating costs. In contrast, a non-pecking order farm is randomly assigned a *PORatio* from 0 to 0.3. It employs less than 30% of its internal capital for operating costs and allocates the remainder to other risky short-term investments. In cases where pecking order farms still have internal funds remaining after operating costs are paid, the residual can be allocated to nonfarm investments.[8]

Signaling Specifications

Borrowers strive to reduce the asymmetric information problem by sending credible, unambiguous signals of their credit risk positions. High profitability, repayment capacity, and effective risk management are examples of signaling instruments. Lenders, in turn, could adopt a risk-adjusted interest rate policy that benefits from improved information. Signaling theory thereby emphasizes the bilateral credit relationships between the borrower and the lender. In this study, the signaling effect is simulated by the lender's use of risk-adjusted interest rates on different farm loans. In the absence of signaling, the interest rate is the same for all borrowers. With the risk-adjusted rate policy, borrowers with low credit risk receive lower rates and high credit risk borrowers receive higher rates (Walraven and Barry, 2004; Goodwin and Mishra, 2000).

The risk-adjusted rate policy is implemented by specifying five credit risk classes,[9] with each having a risk premium that is added to or subtracted from the base rate of the middle class. Following Barry and Ellinger (1989), borrowers' loan rates are determined by their credit score and the classification procedure. The specific premiums are plus or minus 100 and 300 basis points, yielding a 600 basis point range. The base rate, range, and premiums can be adjusted as appropriate. This loan pricing procedure is implemented annually based on the credit

[8] Nonfarm investment is specified as purchasing CDs for pecking order farms, with an annual stable return rate of 5.5%. For farms not following the pecking order financing, nonfarm investment is specified as common stock, with a random one-year return rate between negative 10% and positive 15%.

[9] The credit risk class is based on the credit score model developed by Splett et al. (1994).

score calculated at the end of the prior year. A farm's interest rate would change over time as its risk position changes. In the absence of the signaling effect, the base rate is 50 basis points higher to reflect the lender's favorable response to signaling and remains the same to all borrowers.

Simulation Overview

Each simulated farm business is randomly assigned the characteristics implied by the pecking order and trade-off theories (e.g., *TORatio*, *IR*, and *PORatio*). Those characteristics remain constant over the 10-year period. Alternative combinations of the three theories are created for comparative purposes to seek an optimal combination of financing strategies. The pecking order and signaling theories describe two converse characteristics, while the trade-off theory includes three cases, resulting in a total of 12 scenarios. However, two combinations from the pecking order and trade-off theories are inherently inconsistent.[10] These two combinations, together with the signaling options, yield four unreasonable scenarios which are omitted in the simulation. The remaining eight scenarios, along with their capital structure specifications, are listed in Table 1.

To compare eight financing and lending strategies between the borrower and the lender, each scenario is simulated under homogeneous initial conditions (e.g., identical land composition, asset structure, and capital structure). The representative farms are large cash grain farms with 50/50 rotation of corn and soybeans, located in central Illinois. The forecasted variables include farm loan rates, price, and yield for corn and soybeans.

[10] Because a pecking order farm is opposed to the short-term debt, it will not be a debt-seeking farm. Meanwhile, a farm not following the pecking order financing tends to depend on short-term debt for its short-run financing; it is inconsistent with a debt-avoiding farm.

One thousand farms are generated with the farm size distribution similar to the structural characteristics in Farmdoc's "Financial Characteristics of Illinois Farms 2005" (Table 2). The eight scenarios yield nearly 80,000 farm performance observations for financial and credit analysis. Farm operating performance and financial indicators are computed for 10 years. Once a farm defaults,[11] it stops operation and the balance sheet in that year is recorded to reflect its ending net equity. For example, if a farm defaults at year two, its net equity at the end of year two is considered as the ending net worth.

Forecasting Farm Loan Rates, Yield, and Price

Forecasted loan rates are based on Congressional Budget Office (CBO) projections for 10-year Treasury notes from the years 2007 to 2016. For farm real estate loans, an average spread of 251 basis points between the 10-year Treasury notes and farm real estate loans for the Chicago Fed district for 1997–2006 was added to the 10-year note projections. For operating loans, an average spread of 66 basis points between the farm operating and real estate loans in the Chicago district is added to the farm real estate loan rate projections. Projected rates on intermediate term loans are assumed to be the average of the projected operating and real estate loan rates.

The yield projections for corn and soybeans are based on stationary distributions of commodity price and yield in the future, relative to the National Agricultural Statistics Service 1970–2004 data. Several steps were followed in developing the projections. First, the time series of yields was detrended to calculate a correlation matrix between yields and prices for corn and soybeans.

[11] In this study, default occurs when the farm's total current assets cannot meet the debt service, which includes total short-term debt, total matured interest, and principal needed to be paid at the year end.

Table 1. Scenario Combinations from Different Capital Structure Theories

Scenario No.	Denotation	Adjust to Target D/A^*	Pecking Order Financing	Signaling Effect	*TORatio* Value	*IR* Value	*PORatio* Value
1	TO_PO_SIG	Yes	Yes	Yes	(0.5~0.8)	(0.3~0.7)	(0.7~1.0)
2	TO_PO_sig	Yes	Yes	No	(0.5~0.8)	(0.3~0.7)	(0.7~1.0)
3	TO_po_SIG	Yes	No	Yes	(0.5~0.8)	(0.3~0.7)	(0.0~0.3)
4	TO_po_sig	Yes	No	No	(0.5~0.8)	(0.3~0.7)	(0.0~0.3)
5	to_PO_SIG (debt-avoiding)	No	Yes	Yes	0	(0.0~0.3)	(0.7~1.0)
6	to_PO_sig (debt-avoiding)	No	Yes	No	0	(0.0~0.3)	(0.7~1.0)
7	to_po_SIG (debt-seeking)	No	No	Yes	0	(0.7~1.0)	(0.0~0.3)
8	to_po_sig (debt-seeking)	No	No	No	0	(0.7~1.0)	(0.0~0.3)

Notes: TO = trade-off theory, PO = pecking order theory, and SIG = signaling theory. Capital letter abbreviations indicate that the theory is in effect, and lower-case letter abbreviations imply the theory is not applied in the simulation. *TORatio* = trade-off ratio, *IR* = investment ratio, and *PORatio* = pecking order ratio.

Table 2. Financial Measures for Grain Farms by Farm Size: Tillable Acres (2005)

	Tillable Acres (Number of Farms, % of Sample)			
Financial Measure	**301~600 (*N* = 546, 23%)**	**601~900 (*N* = 538, 23%)**	**901~1,200 (*N* = 420, 18%)**	**> 1,200 (*N* = 720, 30%)**
Assets:				
Cash and Equivalent	5.9	4.7	4.0	3.6
Crops and Feed	11.5	13.8	15.5	17.8
Market Livestock	0.6	0.8	0.5	0.6
All Other Current Assets	3.3	3.8	4.4	5.0
Total Current Assets	21.4	23.1	24.4	27.0
Intermediate Assets	31.7	33.1	33.0	32.6
Fixed Assets	46.9	43.8	42.6	40.4
Total Assets	100.0	100.0	100.0	100.0
Liabilities:				
Operating Short-Term Notes < 1 Yr.	7.5	9.6	9.9	11.7
Current Maturities	1.5	1.9	2.1	2.4
CCC and Other Loans	0.8	0.9	1.2	1.1
All Other Current Liabilities	2.1	2.2	2.3	2.4
Total Current Liabilities	11.8	14.6	15.5	17.6
Intermediate Liabilities	3.4	4.6	5.1	6.3
Long-Term Liabilities	8.5	11.0	10.7	11.4
Total Liabilities	23.8	30.2	31.4	35.4
Net Worth	76.2	69.8	68.6	64.6
Total	100.0	100.0	100.0	100.0
Income Data:				
Value of Farm Production	100.0	100.0	100.0	100.0
Operating Expenses	72.8	69.3	69.1	70.0
Depreciation	6.4	6.8	7.1	7.2
Operating Profit	20.8	23.8	23.8	22.7
Interest Expenses	5.6	5.7	5.4	5.7
Net Farm Income from Operations	15.2	18.1	18.3	17.0
Farm Data:				
Tillable Acres	451	749	1,035	1,840
Tenure	0.25	0.19	0.16	0.14
Absolute Measures, $ (means):				
Assets	1,081,357	1,325,389	1,537,805	2,083,541
Liabilities	190,014	328,893	405,086	659,333
Net Worth	891,343	996,496	1,132,719	1,424,208
Value of Farm Production	147,162	240,937	326,749	523,728
Interest Expense	8,192	13,794	17,600	29,366
Net Farm Income	24,492	45,394	62,271	86,826

Source: Structural characteristics taken from "Financial Characteristics of Illinois Farms 2005," Farmdoc, University of Illinois.

The correlations between the prices and detrended yields were −0.402 for soybeans and −0.343 for corn. Then, multinomial distributions were fitted to the price and detrended yield series. Documented findings indicate that yield distribution can be represented by Weibull distribution (Sherrick et al., 2004) and prices by the lognormal distribution (Schnitkey, Sherrick, and Irwin, 2003). The fitted shape parameter from historical, detrended yield data is 3.66, which enables the Weibull distribution to be treated approximately as normal.[12] Since corn and soybean prices follow the lognormal distribution, the logarithm of price would also follow a normal distribution. Thus, a multinomial distribution containing four correlated random variables (with the same correlation matrix from historical data) is generated with the forecasted prices and yields of corn and soybeans.

The simulation proceeds by reintroducing the estimated trend in crop yields over the 10-year period, and then makes random draws from the correlated price and yield distributions, to determine their outcomes for each year of the simulation period. A second set of random draws occurred in each year to determine each farm's realized yield and price, based on an allowable range of plus or minus 5% for prices and 10% for yields from a uniform distribution centered on the first-round draws. The second draw provided for a limited range of variation of individual farms' prices and yields in each year. However, variations in yields and prices from year to year are the dominant source of risk in the analysis. The yearly forecasted yields and prices, as well as interest rates, are reported in Table 3.

Farm Enterprise Budget

Farm beginning positions are randomly generated based on "Financial Characteristics of Illinois Farms 2005" data (Farmdoc), with the similar levels of farm size, land composition, asset structure, liability structure, and credit situation. Farm business income is composed of crop revenue, government subsidy, off-farm income,[13] and crop insurance proceeds. Since the majority of crop insurance policies sold in Illinois are revenue insurance, crop revenue coverage (CRC) with the coverage levels of 0%, 65%, 75%, and 85% are specified in the model.[14] Crop insurance and government payments thus become major methods of risk management for the simulated farms and offer significant opportunities for smoothing year-to-year variations in crop revenue.

Farm costs include the operating costs, premium paid for crop insurance, interest payments for debt capital, family living expenses, and tax obligations.[15] The estimated operating cost is on a per acre basis.[16] Farm operators bear all operating costs for owned and cash-leased farmland.[17]

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[12] When the shape parameter of the Weibull distribution is between 2 and 5, it can be treated approximately as normal distribution.

[13] Government subsidy is based on the 2002 Farm Bill, including direct payments (DP), countercyclical payments (CCP), and loan deficiency payments (LDP). Off-farm income is generated randomly between 0 and $50,000 for each farm, and is assumed to increase 5% each year in the future.

[14] The 0% coverage level represents farms that do not purchase crop insurance. It is assumed that 5% of farms do not use insurance products, 10% of farms select 65% coverage level, 75% of farms purchase 75% coverage level insurance, and 10% of farms select 85% coverage level.

[15] It is assumed that the crop insurance premium increases 2% in each year; tax obligation is based on a married couple filing jointly with two additional dependents. All tax should be paid at the end of each year; no tax deferral is considered.

[16] Per acre operating cost is divided into three main categories: direct costs (fertilizer, seed, pesticides, and drying & storage); power costs (utilities, machine repair, and fuel & oil expenditures); and overhead costs (hired labor, building repair, and miscellaneous costs). These costs are accrued expenses and do not include opportunity costs such as unpaid labor, equity capital, or management fees, etc. Per acre operating cost at the starting year is assumed to be $179.50 for corn and $111.40 for soybeans. Both increase at 2% in each future year.

[17] Based on surveys from FBFM, it is assumed that 25% of farm businesses use cash lease and 75% use share lease for rented farmland.

Table 3. Forecasted Farm Loan Rates, Price, and Yield for Corn and Soybeans

	Year									
Description	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Operating Loan Rate	7.97	8.17	8.27	8.37	8.37	8.37	8.37	8.37	8.37	8.37
Intermed. Loan Rate	7.64	7.84	7.94	8.04	8.04	8.04	8.04	8.04	8.04	8.04
Real Estate Loan Rate	7.31	7.51	7.61	7.71	7.71	7.71	7.71	7.71	7.71	7.71
Corn Price	1.69	3.07	2.39	2.31	3.12	1.80	2.36	2.29	2.43	1.68
Soybean Price	5.81	7.44	6.92	6.25	6.68	4.53	6.16	4.40	6.42	5.11
Corn Yield	186.84	122.09	159.76	152.99	165.10	164.64	165.46	138.90	160.28	182.61
Soybean Yield	52.25	40.10	45.11	48.91	45.89	48.84	49.86	48.85	48.46	51.93

For share-leased land, farm operators divide the revenue and partial operating costs[18] with land owners at 50/50. Cash rent per acre of $135 is charged at the beginning of the year, and increases at 2% annually. Scale economies are also considered in the operating cost. The coefficient of the scale economies is between 0.97 and 1.03.[19] The premium paid for different CRC coverage levels is calculated with the insurance premium calculator issued by Farmdoc at the University of Illinois.

Interest costs result from using short-term, intermediate, and long-term debt capital. Short-term debt refers to a one-year farm operating loan. Intermediate debt with a seven-year maturity is used for purchasing machinery and buildings, and the real-estate loan for purchasing the farmland is assumed with a 20-year maturity. All debt is borrowed at the beginning of year, and interest and principal payments occur at the year end. Operating loans employ the single payment method, with the principal and interest paid at the year end. Intermediate and long-term debt adopt the equally amortized, fixed payment method.

[18] In the share lease case, farmers share direct costs (fertilizer, seed, pesticides, drying & storage) with the landlords; other operating costs are borne by farm operators.

[19] Middle-sized farms (tillable acres between 400 and 1,000) are assumed to bear the standard per acre cost. Larger farms are assumed to have lower per acre cost, with scale economy coefficients less than 1; smaller farms experience higher cost, with scale economy coefficients larger than 1.

Family living expense is generated randomly between $40,000 and $60,000 at the initial year for each farm, and increases at 5% per year. Property tax is charged at $25 per acre for owned farmland. Federal, state, and self-employment taxes are considered for the income tax payments.

Comparison of the Simulation Output

Growth in net equity is considered as a major goal of the farm business. The average default rate is treated as the standard to evaluate the credit risk for financial institutions, while the risk rating is considered by both parties in the lender-borrower relationship. Farm performances from the eight financing strategy scenarios are compared in two dimensions: by overall 10-year average and by yearly averages of the key financial variables.

Ten-Year Averages

To evaluate farm operating and financial performance from diverse financing strategies and loan rate policies, 10-year averages based on survivors from each financing scenario are examined in Table 4. The results show that signaling benefits both parties in the agricultural credit relationship. Scenarios with the signaling effect indicate a greater average net worth as well as an improved risk rating compared to their nonsignaling counterparts.

Table 4. Selected Simulated Variables by 10-Year Averages

	Operating Performance			Financial Indicators			Scenario Comparisons [c]		
Financing Strategy Scenario	Net Operating Income	Owned Land	Leased Land	Risk Rating [a]	Default Rate [b]	Net Equity	SIG Effect	PO Effect	TO Effect
1 TO_PO_SIG	87,538	229	1,400	2.16	3.34	1,618,973	SIG©1	PO©1	TO©1
	(81,993)	(37)	(312)	(0.56)	(0.21)	(266,693)			
2 TO_PO_sig	80,787	226	1,378	2.24	3.54	1,601,357	SIG©1	PO©2	TO©2
	(80,386)	(35)	(297)	(0.61)	(0.23)	(252,761)			
3 TO_po_SIG	80,103	223	1,364	2.34	3.48	1,601,044	SIG©2	PO©1	TO©3
	(79,336)	(33)	(282)	(0.56)	(0.23)	(251,787)			
4 TO_po_sig	73,913	221	1,350	2.43	3.65	1,584,985	SIG©2	PO©2	TO©4
	(78,038)	(31)	(269)	(0.63)	(0.22)	(238,131)			
5 to_PO_SIG	72,207	207	1,050	1.99	2.91	1,556,727	SIG©3		TO©1
	(60,887)	(26)	(131)	(0.52)	(0.18)	(208,921)			
6 to_PO_sig	68,973	205	1,043	2.03	3.05	1,549,904	SIG©3		TO©2
	(60,331)	(24)	(122)	(0.55)	(0.18)	(202,356)			
7 to_po_SIG	79,676	293	1,401	2.74	3.78	1,673.922	SIG©4		TO©3
	(87,180)	(57)	(262)	(0.71)	(0.27)	(318,511)			
8 to_po_sig	71,672	286	1,377	2.81	4.01	1,649,148	SIG©4		TO©4
	(85,107)	(53)	(251)	(0.73)	(0.26)	(302,998)			

Notes: Values in parentheses are standard deviations based on 10-year observations. Pairwise *t*-tests of mean difference for signaling and pecking order effects are significant at the 5% level for all variables, except the mean difference of default rate. The mean difference *t*-tests for trade-off comparisons are significant at the 1% level for operating performance variables and net equity; however, the *t*-tests of mean net operating income and default rate in the comparison of TO©3 and TO©4 groups are not significant.

[a] Risk rating is represented by average credit score, with a lower credit score implying a lower credit risk farm.

[b] Default rate is calculated as total number of default farms over the 10-year period divided by 1,000 farms.

[c] In column scenario comparisons, same denotations imply that the specific financing or lending characteristics can be compared in those pairs. For example, two "PO©1" in the PO Effect column means that the pecking order characteristic could be compared in TO_PO_SIG and TO_po_SIG scenarios.

Over 10 years, the average net equity for signaling farms is $17,616, in total, more than nonsignaling farms when both scenarios adopt the trade-off and pecking order financing strategies. The difference from the signaling effect goes to $6,824 per year for debt-avoiding farms and $24,774 per year for debt-seeking farms given the same pecking order conditions. The differences primarily reflect the effects of the lender's more favorable risk-adjusted rate policy, in which the base rate is 50 basis points less than the non-risk-adjusted rate. Farms in the signaling group on average achieve better risk rating and lower default rates than those not following the signaling theory. Hence, the signaling process plays a positive role in the agricultural credit relationship. The signaling behavior not only increases farms' ending net worth but also promotes their incentives to send favorable signals to strive for lower farm loan rates. Meanwhile, the lower default rate from borrowers also benefits lending institutions, enabling them to maintain a loan portfolio with lower default rates over time.

The average net equity, risk rating, and default rate for trade-off farms are in the middle of debt-avoiding and debt-seeking farms. This location is consistent with the expectation that trade-off farmers seek a moderate development. By adjusting toward a target debt-to-asset ratio, trade-off farmers effectively balance their risk and returns. Trade-off farmers avoid excessively high debts, which may create financial distress for their business. Under higher debt-to-asset ratios, farm businesses may not fully repay matured principal and interest, which could incur loan default (resulting in financial stress or potential bankruptcy). However, keeping a certain amount of debt capital on the balance sheet would benefit trade-off farmers by having to pay fewer taxes.

The economic impact from the pecking order theory is analyzed through the comparison between scenarios 1 and 3 and scenarios 2 and 4, with the difference in farm performance results solely from the pecking order financing. It is obvious that pecking order farms borrow less short-term debt than their counterparts, and their ending net worth levels, risk ratings, and default rates are generally in advantageous positions over the simulation period. Therefore, the pecking order financing improves a farm's short-term financial performance; it is an efficient financing strategy for a farm's liquidity management.

Most of the performance differences are significant at conventional confidence levels. Pairwise t-tests of mean differences of the 10-year averages for the signaling and pecking order effects are significant at the 5% level for all the performance indicators except the mean differences for the default rate. The mean difference t-tests for trade-off comparisons are significant at the 1% level for the operating performance variables and net equity. However, the test results for net operating income and the default rate are not significant for two of the four comparisons (TO©3 and TO©4).

Yearly Averages

As shown in Figure 1, the time period is volatile with wide swings in crop sales. Combining all income and cost factors, the yearly predicted per acre income indicates that government payments substantially increase farm business income, while the use of crop insurance and the countercyclical portion of government payments have major stabilizing effects. Especially important is the smoothing of the abrupt swings in per acre income.

Based on the same initial conditions, farms employing different financial strategies experience a parallel development pattern. The average net equity, risk rating, and default rate in each year are plotted in panels A, B, and C, respectively, of Figure 2. As shown by panel A, debt-seeking farms build the largest net equity due to their aggressive investments. Debt-avoiding farms accumulate the least equity amounts.

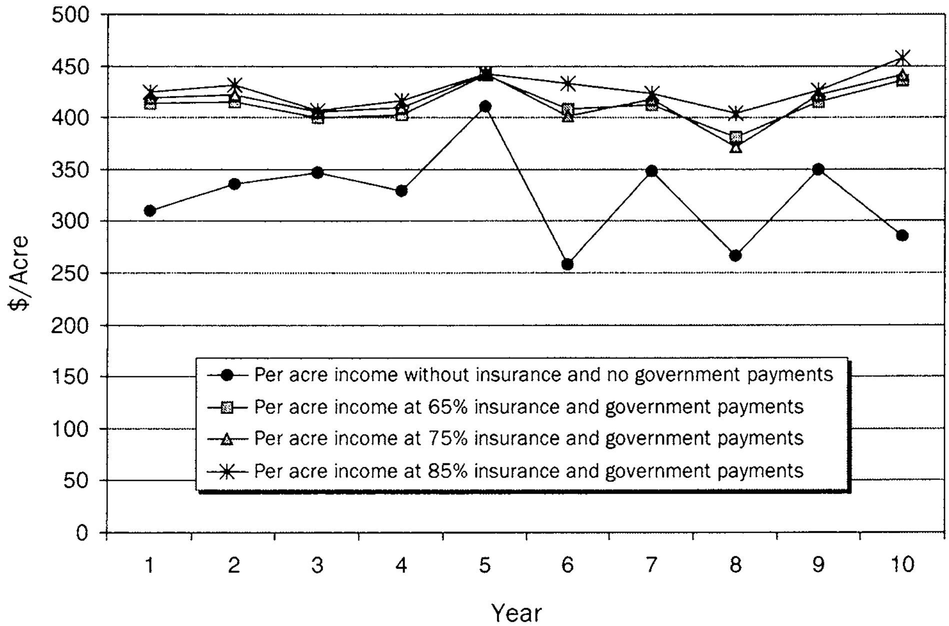

Figure 1. Predicted Yearly per Acre Income Under Different Insurance Levels

For trade-off farms, those that follow the pecking order strategy acquire more equity than non-pecking order farms.

The order of the risk rating curves from each financing scenario (panel B) is similar to the ranking of the net equity. Debt-seeking farms experience the highest credit risk resulting from excessive debt. Debt-avoiding farmers received the highest credit evaluation. Trade-off farms fall in the middle, with a lower credit risk rating for the pecking order farms within the trade-off group.

Figure 2 also describes farms' accumulated default rate at each year in different simulation scenarios (panel C). Initiated at homogeneous starting positions, farms default less during the first three years due to improved farm income. From the fourth year, debt-seeking farms consistently incur the highest default rate, while debt-avoiding farms have the lowest default rates with the signaling paradigm performing better than their counterparts. The accumulated default rate for trade-off farms is in-between the rates for the debt-seeking and debt-avoiding farms, with some switching between the pecking order and the signaling rates depending on conditions in a specific year.

Conclusion

This study applies and simulates the effects of three capital structure theories with the related financing strategies on farm businesses and agricultural credit relationships. The simulation results from different financing and lending strategies provide insights to both farm borrowers and lenders on how to improve financial management, effectively manage the credit risk, and develop a reliable borrower-lender relationship in agricultural capital markets.

The insight gained from the pecking order financing is that farms may finance their short-term financial needs by internal funds, which is an effective approach for liquidity management. The trade-off theory allows farm businesses to invest at steady and financially healthy speeds; their ending net worth is larger than

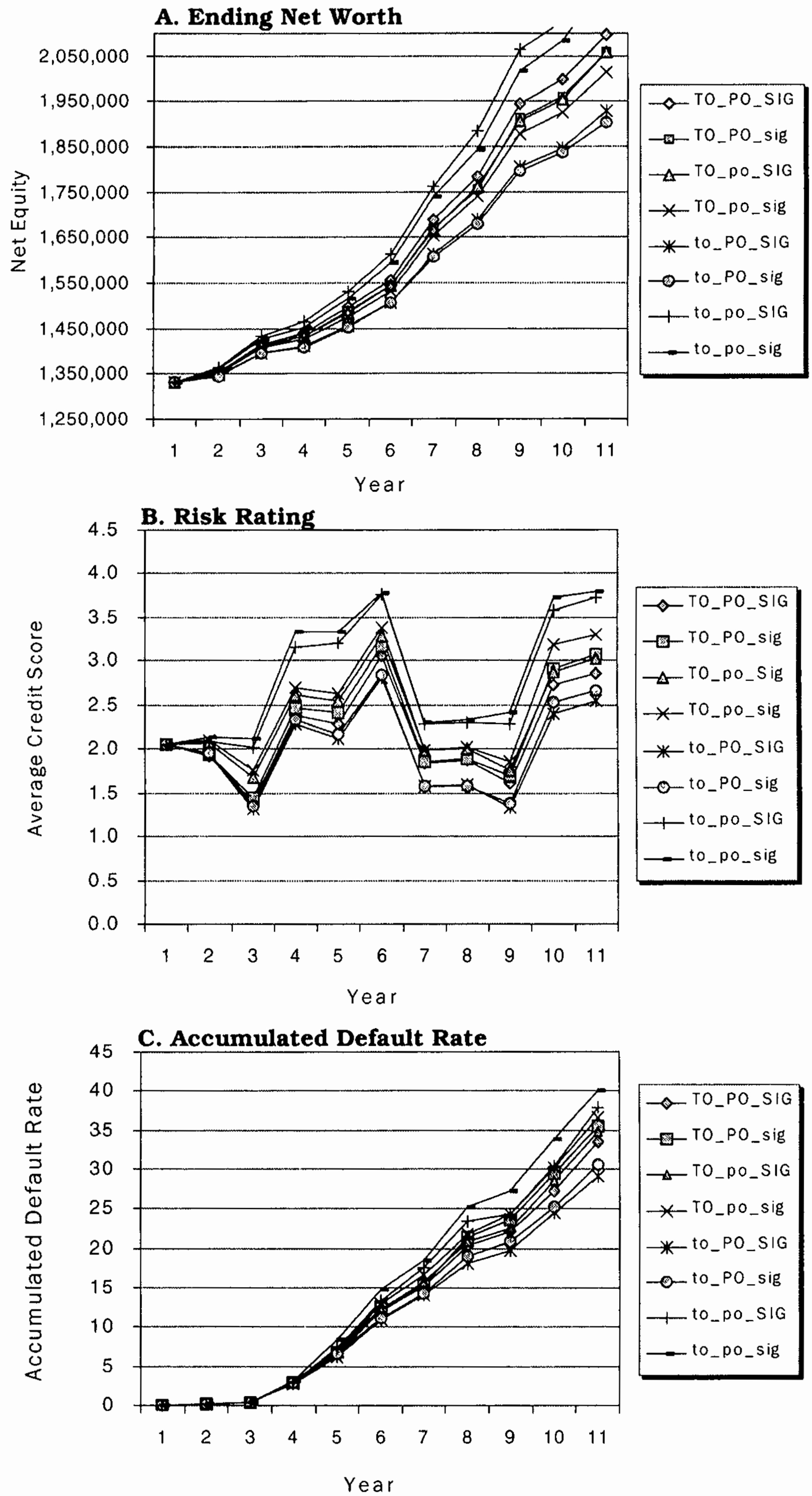

Figure 2. Yearly Average Net Worth, Risk Rating, and Accumulated Default Rate in Different Financial Scenarios

debt-avoiding farms but less than debt-seeking farms. Although debt-seeking farms accumulate the largest net equity through aggressive investments, they are punished by an inferior risk rating and the highest default rate.

Finally, the simulation results demonstrate that financial scenarios with the signaling mechanism dominate their counterparts. The signaling effect between the borrower and lender not only benefits low credit risk borrowers with a lower farm loan rate, but also enables lending institutions to distinguish among borrowers at different credit risk levels. Therefore, the signaling tactic and effective communication between the borrower and lender should be recommended in the agricultural credit relationship. In all cases, risk management through the use of crop insurance and participation in government programs has important stabilizing effects on net farm income.

Each financing tactic implied by different capital structure theories is essential for financial management of farm businesses. Different financial strategy combinations may be preferred by farm businesses based on their risk attitudes. Joint application of the pecking order, trade-off, and the signaling theory (TO_PO_SIG) would benefit farm businesses not only by faster growth of their net equity, but also financial safety, which may lower the overall risk, thereby enabling farm businesses to obtain external capital smoothly, and decrease their financing cost.

Another goal of our study was to build upon previous and related studies in agricultural finance by expanding the properties of multi-period, stochastic, farm-level simulations to include elements of financial behavior, investment dynamics, and the interrelated approaches to managing capital structure. The simulation realizes the concomitance of the pecking order theory and trade-off theory for farm business by Barry, Bierlen, and Sotomayor (2000), the complementary effects of the pecking order and signaling effect for firms by Shenoy and Koch (1996), and the coexistence of the pecking order, trade-off, and the signaling theory by Zhao, Barry, and Katchova (2008). The result is a more realistic, plausible tool for financial planning and projections.

The methodology achieved this goal through a combination of conceptual and empirical specifications based on key assumptions, projections, decision rules, and financial benchmarks derived from observed business performance. Yet, the different financial scenarios considered in this study only reflect the simplified implications of the pecking order, trade-off, and signaling theories.

Future studies, for example, could relax some of the assumptions, broaden the range of farm types, and extend the refinancing process in the agricultural credit relationship. Since many financially stressed farms have continued their operations and have survived and thrived in the business world, the addition of refinancing, lender forbearance, and loan workouts in the simulation would contribute significantly to this kind of research.

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An Excel-Based Decision Aid for Evaluating Financing Alternatives and the Marginal Cost of Capital

Jeffrey R. Stokes and Jayson K. Harper

Abstract

For agricultural businesses, managing debt capital means choosing from among myriad sources and terms for financing for inputs, machinery, equipment, and land. Providers of debt capital, including input suppliers, equipment dealers, commercial banks, and the Farm Credit System, offer differing interest rates, rebates, points, and other non-interest costs. Microsoft Excel™-based financing decision aids were developed to help agricultural decision makers evaluate options by determining the true cost of capital from supplier financing, machinery and equipment financing, and real estate purchases. These same tools were also used as a teaching aid in senior-level university courses in farm management and agricultural finance to reinforce agricultural cost of capital concepts.

Key words: annual effective rate, annual percentage rate, cost of capital, decision aid

Agricultural businesses rely on borrowed capital for inputs, machinery, equipment, and land. Debt capital is typically a less expensive source of capital (compared to equity capital) and can accelerate the rate of growth in equity capital. However, use of debt capital increases the risk of equity loss, and its management is a critical farm business management function.

Managing debt capital for a farm or other agribusiness requires choosing from among multiple financing sources including input suppliers, equipment manufacturers, commercial banks, and the Farm Credit System. Each source likely offers different loan terms including contractual interest rates, rebates, points, and other non-interest costs.

Educational efforts that teach agricultural producers and agribusiness management undergraduate students how to evaluate financing alternatives are important so they can calculate and better understand the true marginal cost of debt capital. In this way, financing options can be properly compared and ranked based on cost. In addition, this knowledge aids in risk management because equity loss only occurs when the farm's cost of debt capital exceeds the farm's rate of return of farm assets.

In response to this need, the Agricultural Cost of Capital Calculator (hereafter "calculator") was developed to be easy to use and have the flexibility to encourage users to compare financing alternatives. The calculator was developed using Microsoft Excel™ and Visual Basic for Applications (VBA), making it accessible

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to a wide range of users. It is available on the Penn State Farm Management Extension website at {http://farmmanagement.aers.psu.edu} under "Management Tools."

In this paper, we discuss some conceptual issues as they relate to the calculation of the marginal cost of capital for short-, intermediate-, and long-term financing situations. The calculator is described in this context and detailed examples of each type of situation are presented. Our experiences using the calculator in extension settings and upper-level undergraduate courses in finance and farm management are also discussed. It should be stressed that the calculator is not a substitute for cost of capital curricula, but rather a complement. Our experience indicates that getting students to understand how to calculate the cost of capital is a necessary first step, and the calculator merely reinforces their understanding of the tradeoffs involved. The major contribution of the calculator for producers in real-world situations is that it makes the evaluation of numerous financing alternatives relatively painless.

Agricultural Cost of Capital Calculator

The calculator is divided into three decision modules appearing on three Excel™ worksheets (see Figures 1, 2, and 3 for screenshots of each of the three modules). These modules are shown as tabs along the bottom of the screen in Excel™. Navigation through the modules can be done by using the arrow icons in the lower left corner or by clicking on the tabs themselves.

In each module, users enter data relating to their financing alternative in yellow-shaded boxes (all of the other cells except those used by the macros are "locked" to protect formulas and formats). After entering their information in the yellow-shaded boxes, users then click on the appropriate boxes to run the macros programmed in VBA. Any financing parameter can be changed and the calculator can be rerun at any time. Users can also clear all information from a particular module by clicking on the "Reset calculation" box.

In the case of the short-term financing module, the output includes the calculation of a critical interest rate for a borrowing comparison that shows the effective interest rate charged for payment on the due date and an estimate of the annual cost of not taking the discount. For the intermediate-term and long-term financing modules, output includes calculation of the periodic interest rate, annual percentage rate (APR), annual effective rate, and the loan amortization table.

Evaluating Short-Term Financing (Trade Credit)

Trade credit consists of financing provided to agricultural producers by merchants, dealers, and other agribusiness firms, and aside from direct personal loans, is perhaps the oldest form of credit known (Barry et al., 2000, pp. 503–504). The terms of this type of credit usually involve the specification of a percentage discount, the discount period, and the number of days in which full payment is expected. From the perspective of an input supplier, the convenience offered by trade credit can greatly facilitate sales and provide a competitive advantage. Although it is a widely used merchandising practice employed by agribusinesses for sale of inputs such as feed, seed, and fertilizer, farmers are generally unaware of the high underlying implicit cost of capital involved with trade credit.

The first decision aid module uses the economic concept of opportunity cost and the financial concept of time value of money to determine the cost of capital from supplier financing. Many agricultural input suppliers offer terms of sale that allow producers to take advantage of cash discounts for early payment. Such terms of sale typically have a very high implicit cost of capital. Numerical and graphical outputs allow a producer to determine the cost of financing inputs under any terms of sale offered. The module calculates a critical interest rate for a borrowing comparison, showing the effective interest rate charged for payment on the due date and an estimate of the annualized cost interpreted as an opportunity cost of not taking the discount. If cash is not available to take the discount within the time frame it is available and money could be borrowed elsewhere at a rate less than this critical rate, it would be to the producer's advantage to do so.

A textbook example of trade credit terms are 2/10 net 30, which means buyers may deduct 2% from their invoice if the balance is paid within 10 days or the full amount should be paid by no later than 30 days. This calculator can also be used to negotiate cash discounts with merchants instead of using a credit card. Merchants pay credit card companies an "interchange fee" of from 1–6% which the purchaser could evaluate as an x%/1, net 30 trade credit policy.

Let d represent the percentage cash discount, m represent the number of days after a sale that the discount may be taken, and n represent the number of days the buyer has to pay the invoice in full. Using this notation, the terms of sale offered by the firm are characterized as a d/m net n policy. Further, let S represent the dollar value of a sale to a customer. For a customer opting to take the cash discount, it is optimal to do so on day m paying $(1 - d)S$. For a customer not interested in taking the discount, S must be paid in full on day n.

Using the m and n points in time for reference, a buyer who opts to not take a discount must at least be indifferent to taking the discount on a present-value basis. Let i be the firm's annual cost of financing buyer purchases for a 360-day year, implying:[1]

$$(1)\qquad \frac{(1-d)S}{\left(1+\frac{i}{360}\right)^{m}} = \frac{S}{\left(1+\frac{i}{360}\right)^{n}}.$$

Solving for i in equation (1) gives the annualized cost of capital. In doing so, most textbooks make use of the approximation

$$\left(1+\frac{i}{360}\right)^{x} = 1+\frac{i}{360}x$$

for any value of x. Therefore, we have

$$(2)\qquad i = \left(\frac{d}{1-d}\right)\left(\frac{360}{n-m}\right).$$

Equation (2) shows that the annual cost of financing buyer purchases is the product of the daily cost (the first parenthetical term) and the number of periods of length $n - m$ in a 360-day year (the second parenthetical term). For example, a 2/10 net 30 policy has $d = 0.02$, $n = 30$, and $m = 10$, so that $i = 36.73\%$.

A screenshot of the cost of capital calculator for a 5/15 net 45 trade credit policy is shown in Figure 1. The user inputs d, m, and n, and additionally enters an average dollar amount for purchases and the typical annual frequency of purchases falling under this type of financing. A series of Annualized Costs of Capital are generated, which shows the daily impact of missing a cash discount.

For example, paying on day 16 and therefore missing a 5% discount is tantamount to financing a purchase for one day at an annualized cost of over 1,900%. The series is depicted graphically, showing that if a discount is missed, it is best to pay on the last day (in this case day 45) with an annualized cost of 64%. Also shown is the annual dollar amount lost from missing cash discounts, which in this case is \$300 (5% × \$500 × 12) given the magnitude of the typical purchase for which the cash discount is made available.

[1] The 360-day year assumption makes calculations easier since 360 is divisible by many more numbers than 365. The assumption is also consistent with most textbook treatments of terms-of-sale decisions.

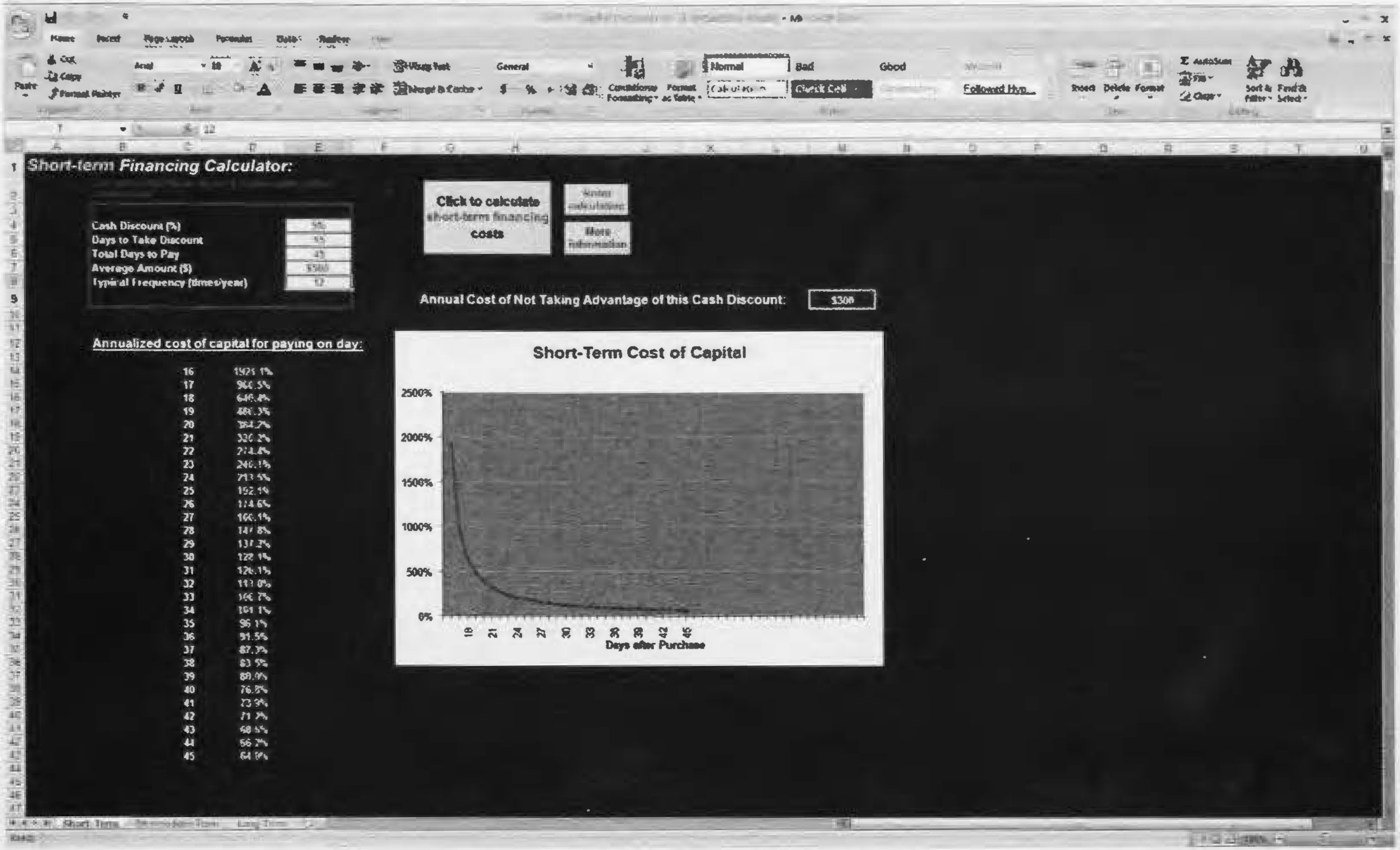

Figure 1. Agricultural Cost of Capital Calculator Screenshot for Short-Term Financing Module

Comparing Intermediate-Term Financing Options

The second decision aid module (Figure 2) applies time value of money concepts to loans provided by commercial lenders and automobile and machinery dealerships for trucks, tractors, and equipment used by the farm business. Alternative sources of intermediate-term financing typically have different contractual interest rates and non-interest costs, making direct comparisons difficult. The terms of this type of credit usually involve the specification of the financed amount and include the negotiation of the purchase price, trade-in value, down payment, and any rebates.

Often other costs, such as document preparation, taxes, title, and license fees, are included in the financed amount. One consideration in comparing different financing options is that dealers usually offer either financing or rebates. In some cases it may make more sense to finance the purchase elsewhere at a higher interest rate and take the dealer rebate than it is to take a lower percentage rate for borrowed capital from the dealer. The choice among financing alternatives can be quite difficult; the decision aid will allow the producer to enter the borrowing terms for each alternative so the costs of capital can be compared.

For both intermediate- and long-term (discussed below) loans, the effect of non-interest costs can have a major impact on the true marginal cost of capital. The oft-quoted annual percentage rate (APR) reported under the Federal Truth in Lending Act represents the total financing cost of credit expressed as a percent per annum. The APR must be disclosed to the borrower—but unfortunately, this is typically done when selecting a financing source is no longer an issue (e.g., at closing). In addition, a better estimate of the marginal cost of capital than APR is the annual effective rate which includes the impact of compounding. Even so, the actuarial rate forms the base cost of capital for both APR and the annual effective rate. The actuarial rate is the discount rate that equates to zero the sum of the present values of all cash flows associated with the loan transaction (Barry et al., 2000, p. 402) including non-interest costs. A proper comparison between loans with different terms and non-interest costs is accomplished by compounding the actuarial rate over the number of conversion periods within a year to determine the annual effective rate (Barry et al., p. 407).

The intermediate financing module allows users to analyze rebates and competing financing terms. As an example, consider a dealer who offers a rebate of \$500 on a new \$40,000 farm truck. If the rebate is not taken, the dealer offers three years of financing at an annual contractual rate of 3% with monthly payments. Alternatively, if the rebate is taken, the dealer expects a 5% annual contractual rate for five years. In this case, the dealer is less generous with the rate of interest but is willing to stretch out the repayment period, which has the effect of lowering the monthly payments. In addition, the dealer charges \$100 for document preparation and \$2,500 for tax, title, and license irrespective of whether the rebate is taken or not. These non-interest costs, however, are associated with this financing source and must be included in the calculation of the marginal cost of capital. Further assume the farmer also has a combination of down payment and trade-in amounting to \$10,000.

The \$2,600 in additional cost has the effect of raising the cost of financing above the stated rates of interest of 3% or 5%. How much can be determined by computing the actuarial rate of interest? As noted above, the actuarial rate of interest is the per period percentage cost of capital that includes non-interest as well as interest costs. In effect, calculating the actuarial rate of interest embeds any non-interest costs into the contractual rate of interest.

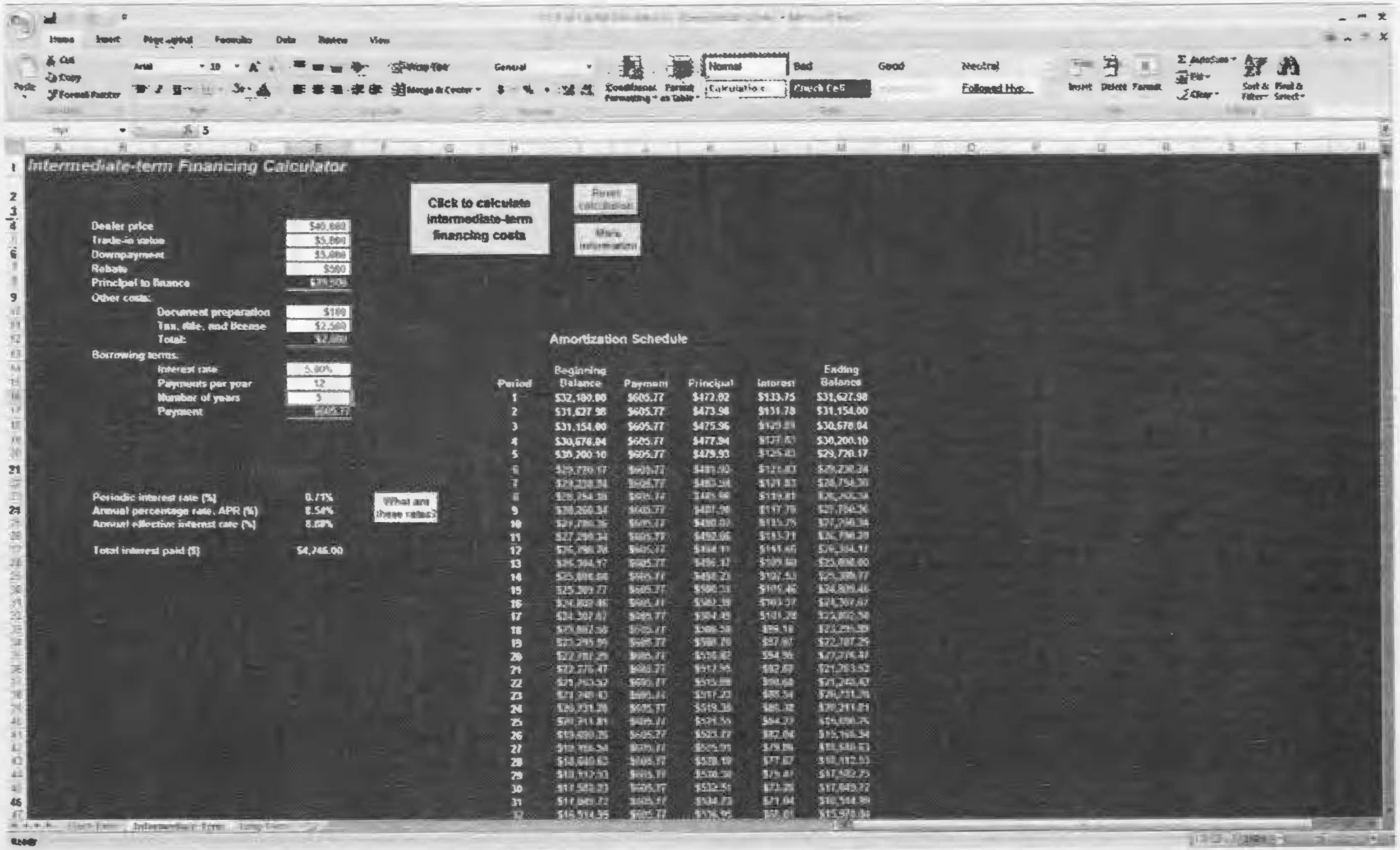

Figure 2. Agricultural Cost of Capital Calculator Screenshot for Intermediate-Term Financing Module

The formula for determining the actuarial rate is similar to that for determining an internal rate of return. Let V be the principal amount, A be the periodic payment associated with the amortized principal plus any non-interest costs, and let i_{ACT} be the actuarial rate of interest. The formula is then specified as

$$(3) \qquad V = \frac{A}{1 + i_{ACT}} + \frac{A}{(1 + i_{ACT})^2} + \ldots + \frac{A}{(1 + i_{ACT})^{mN}}$$

for a constant payment note with payment frequency m lasting N years.

In the example assuming no rebate is taken, V is $30,000 ($40,000 dealer price less $10,000 trade-in and down payment), and A = $948.05, which is the amortized principal of $30,000 plus the $2,600 in non-interest costs over the period of three years with monthly payments. When inserting these values into equation (3), an actuarial rate of interest equal to 0.71% per month results.

The APR is simply the actuarial rate multiplied by the payment frequency of 12, which results in 8.57%. Since the APR ignores compounding, the annual effective rate can be determined by adding one to the actuarial rate, raising the sum to the 12th power and then subtracting one. Doing so results in an annual effective rate equal to 8.92%.

The results of the alternative of taking the cash rebate but paying the higher interest rate for a longer period of time are shown in Figure 2. The monthly payment is lower at $605.77, but the longer terms imply more total interest expense ($4,246.00 vs. $1,529.71). The annual effective rate for this option is 8.88%, or 0.04% lower than the previously calculated 8.92%. Because the annual effective rates are comparable, the choice of financing option likely depends on other features of the problem. Some of these features can be calculated directly, such as total interest paid, which clearly favors the note with the shorter term.

Alternatively, cash flow considerations may preclude the selection note with the shorter term since the monthly payments are about $340 higher. This brings up an important point in that the calculator greatly facilitates the computation of the marginal cost of capital, but cannot make the decision for the farmer. Moreover, the calculator can only quantify those costs that are estimable.

Comparing Long-Term Financing Alternatives

The third decision aid module (Figure 3) helps users evaluate the cost of long-term credit like that provided by commercial lenders and the Farm Credit System for land and buildings. The terms of this type of credit typically involve the specification of the financed amount, repayment period, and contractual interest rate, along with any points and potentially a balloon payment. A point is simply 1% of the loan amount, and is paid to the lender in exchange for a lower contractual interest rate. A balloon payment is simply interest on a non-amortized portion of the principal calculated as the contractual interest rate times the amount ballooned. The ballooned amount is repaid in full when the loan matures.

Often closing costs—i.e., items such as document preparation, title search, appraisals, credit reports, surveys, and real estate transfer taxes—are included in the financed amount. Because the magnitudes of these non-interest costs tend to be specific to a financing source, they make the comparison between financing sources difficult. In addition, Farm Credit System borrowers must buy stock and will receive patronage while they are a customer and the calculator accommodates these features. Users can select a "Farm Credit System" option so that the effect of stock requirements and patronage dividends are included in the calculation. These calculations are based on the assumptions that the stock purchase is 1% of the loan amount up to a maximum of $1,000, and the patronage

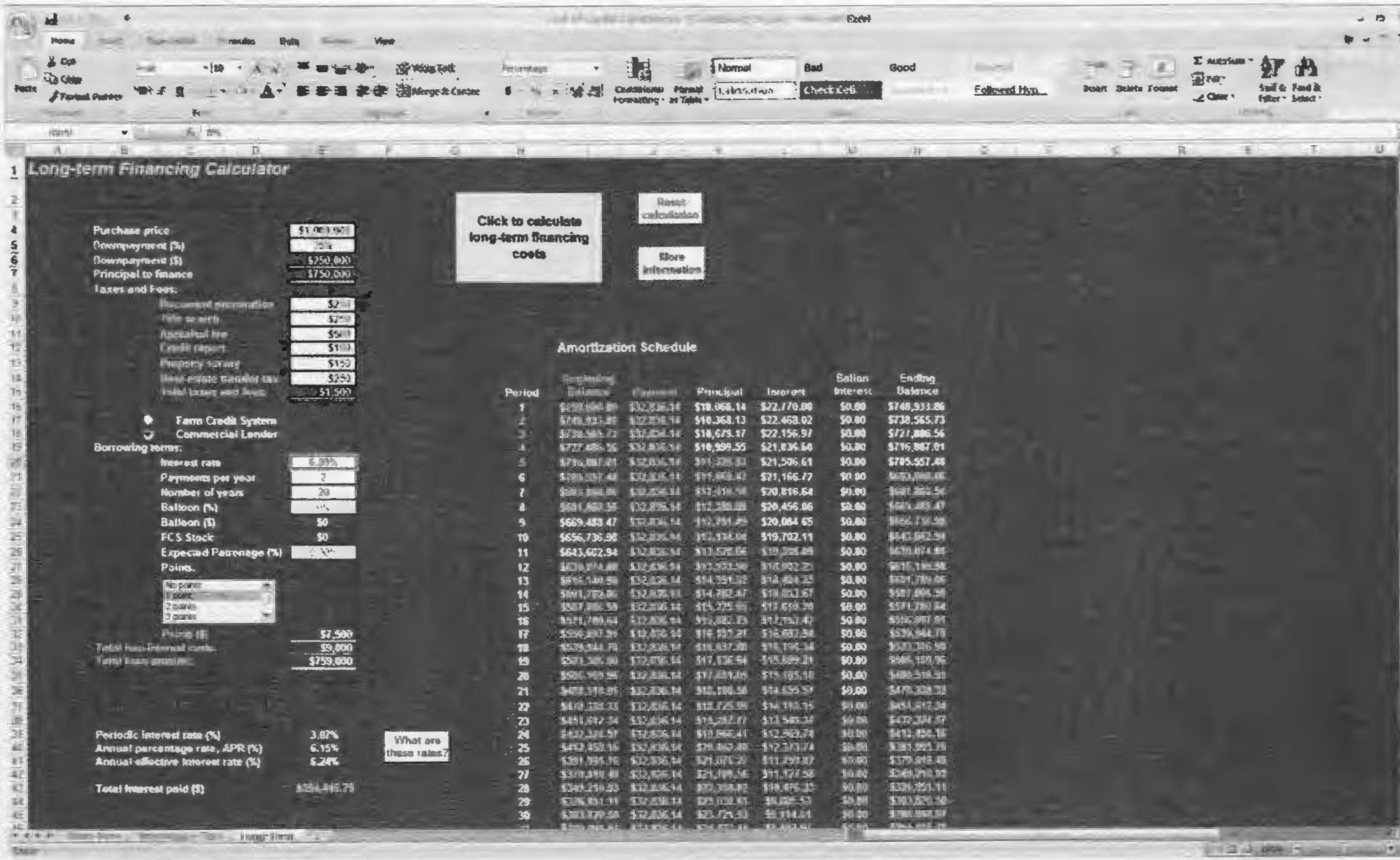

Figure 3. Agricultural Cost of Capital Calculator Screenshot for Long-Term Financing Module

dividend is a percentage of interest expense supplied by the user. Real estate purchases are typically for longer periods of time and bring with them some additional considerations as well. For example, ballooning a portion of a note or buying down the interest rate by paying points are common features of loan products. Nevertheless, equation (3) still forms the basis for the calculation of the marginal cost of capital.

As an example, consider two competing ways to finance the purchase of $1 million of farmland. The specific costs attributable to the two financing sources are presented in Table 1.

The commercial bank loan is for a lower contractual interest rate, but at the expense of a point, while the Farm Credit System loan necessitates a 10% balloon and a stock purchase which entitles the borrower to patronage during the life of the loan. Non-interest costs between the two sources also differ. Given the assumptions in Table 1, the APR on the note with the commercial lender is 6.15% while the annual effective rate is 6.24%. Total interest paid is calculated as $554,445.75 over the term of the note. By contrast, financing the purchase through the Farm Credit System would result in an APR of 5.84% and an annual effective rate of 6.05% and total interest of $773,321.13. The higher interest expense is due to the assumption of a 10% balloon and higher contractual interest rate. Even so, the loan carries a lower overall marginal cost of capital due primarily to the patronage dividend.

User Experience and Conclusions

The Agricultural Cost of Capital Calculator has been used both in extension and undergraduate teaching settings. Since its release in 2007, the model has been used in extension in-service training sessions with county educators and at extension meetings for producer audiences.

Table 1. Example Loan Requirements for $1 Million of Farmland Investment

Item	Commercial Bank	Farm Credit System
Down payment percentage	25%	25%
Taxes and Fees:		
▸ Document preparation	$250	$200
▸ Title search	$250	$200
▸ Appraisal	$500	$300
▸ Credit report	$100	$100
▸ Property survey	$150	$150
▸ Real estate transfer tax	$250	$250
Contractual interest rate	6%	7.75%
Payment frequency	semi-annual	monthly
Years	20	20
Balloon percentage	0%	10%
Stock requirement	$0	$1,000
Annual Patronage	0%	20%
Points	1%	0%

Its capabilities have also been demonstrated at the Pennsylvania Agricultural Bankers conference and at the National Extension Risk Management Education conference.

Extension evaluations of the overall quality of in-service training sessions using the Agricultural Cost of Capital Calculator averaged 6.7 on a 7-point scale. Extension educators felt that the value of the financing calculator to their county clientele and educational program was also 6.7 on a 7-point scale.

In terms of educators' understanding of issues relating to short-term credit, they rated their knowledge at 5.3 on a 7-point scale before the training session and 6.5 afterward. For their understanding of issues relating to intermediate-term credit, they rated their knowledge at 5.5 on a 7-point scale before the training session and 6.3 afterward.

Concerning educators' understanding of issues relating to long-term credit, they rated their knowledge at 6.2 on a 7-point scale prior to the training session and 5.8 afterward. This drop can be explained by the relatively high knowledge by participants of typical long-term loans such as home mortgages, but their relative unfamiliarity with the wide range of options available in agricultural loans including points and balloon payments and the issues relating to Farm Credit loans (including stock requirements and patronage dividends).

Our experience using the calculator in senior-level undergraduate courses in farm management and agricultural finance has also been positive. The vast majority of the students in these classes had previously taken a junior-level course in finance. To test the effectiveness of the model as a teaching aid, students were given a pre-test covering specific short-, intermediate-, and long-term financing options (such as those presented as examples above), and none were able to correctly answer any of the questions. After classroom instruction on how to calculate the cost of capital and instruction on the use of the calculator, students retook the pre-test, and 84% were able to correctly determine the cost of capital.

As noted above, the calculator is not a substitute for teaching students about the nature of economic tradeoffs and how to quantify them. Rather, the calculator has been successfully used after students have had instruction in the development and application of equations (1)–(3). In this way, the calculator reinforces the students' ability to understand the economic tradeoffs involved with various financing options and the impact of various loan provisions on the effective rate of interest faced by borrowers.

In addition, the calculator provides a mechanism for evaluating numerous financing sources in case settings that would be very difficult to achieve otherwise. For example, changing the payment frequency from annual to monthly would require a substantial investment in time using equation (3). With the calculator, the effect of repayment frequency on the effective interest rate is quickly determined.

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Announcement of The W.I. Myers Prize in Agricultural Finance

To encourage the publication of peer-reviewed research, Myers Endowment funds will be used to support two awards starting with the Spring 2006 issue of ***Agricultural Finance Review***. The prizes will include a monetary award as well as a certificate. Selected by the editors and on nomination by subscribers to *AFR*, the two awards will be for:

- *Overall Best Journal Article*, and
- *Best Journal Article Authored by a Student.*

All articles are eligible for an award, including invited papers and papers submitted for special issues. There are no specific criteria for determining what constitutes a "best" journal article except that it will be known to be best once read. The student award must have the student as senior author, must have been written principally by the student, and must contain thesis, dissertation, or any other research originated by the student either independently or under the advisement of a faculty. The two awards are mutually exclusive, meaning that if the student award is also the best journal article, only the best journal article award will be given. The winners of the award will be announced annually in the Spring issue of ***Agricultural Finance Review.***

The W.I. Myers Professorship of Agricultural Finance

Gifts made to Cornell in W.I. Myers' name help underwrite ***Agricultural Finance Review*** for the continued dissemination of research in agricultural finance and to grow the discipline into other fields of study such as micro finance, development economics, agricultural business, and risk management. Following his death at the age of 84 in 1976, Cornell University and friends established an endowment in Myers' name for the sole purpose of promoting his legacy and dedication to the practice and scholarship of agricultural finance. As the mandate for the endowment states, "the need for research is growing rapidly in the area of capital management of farm firms and agribusiness firms and must continue in the decades ahead to ensure a sound American agricultural system."

The Myers Chair was held first by Robert S. Smith on a part-time basis. In 1981, Dr. John R. Brake was recruited from Michigan State University to take the chair, which he held until his retirement in 1996. His successor, Dr. Eddy LaDue, then held the chair for 10 years until his retirement in 2006.

Calum G. Turvey
W.I. Myers Professor of Agricultural Finance
Editor, *Agricultural Finance Review*

Reviewers

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The effectiveness of this publication depends on its support by agricultural finance professionals. The editorial staff gratefully acknowledges the following reviewers for contributing to the quality and success of the *Journal*:

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