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WP 2004-08
May 2004



Working Paper

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Credit Risk Migration Experienced By Agricultural Lenders

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Credit Risk Migration Experienced By Agricultural Lenders

By

Brent A. Gloy, Eddy L. LaDue and Michael A. Gunderson*

ABSTRACT: Loan records and lender credit risk classifications are used to examine agricultural credit risk migration. The results include estimates of the likelihood of borrowers transitioning among five credit risk tiers. The paper also examines factors that influence or predict credit risk migration and its impact on loan pricing.

Keywords: credit risk, agricultural lending, credit risk migration, credit quality

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Credit Risk Migration Experienced By Agricultural Lenders

Introduction

Predicting changes in portfolio credit risk is often based on the credit risk migration of individual loans. Credit risk migration, per se, has received a great deal of academic study. Numerous studies have examined how credit ratings assigned to publicly traded bonds by ratings agencies such as Moody's and Standard & Poor's transition over time. With respect to commercial and agricultural lending, several factors have limited the number of studies that report how loan quality ratings transition over time. These limitations arise from the proprietary nature of the data, the small portfolios and thus sample size for many lenders, and the tendency for the lenders to change their rating systems and approaches over time.

Barry, Escalante, and Ellinger have worked to overcome data deficiencies by estimating credit ratings from farm record keeping association data and examining how these estimated ratings change over time. While this approach is quite reasonable, it is not clear how closely the estimated credit ratings correspond to the internal credit ratings assigned by agricultural lenders. The credit risk evaluation process, the factors considered in credit evaluation, and the loan officer's involvement in the process all make it unlikely that internal credit risk ratings will exhibit as much variability as those estimated from external farm financial data.

When originating a loan, the lender decides whether the borrower represents an acceptable credit risk. In some cases this may require a great deal of financial information, and in other situations it may require very little financial information. Although most lenders will undertake annual reviews of credit quality, based on the

lender's assessment of the costs of benefits of such reviews and analyses, some borrowers may be subject to more frequent and strenuous reviews than others. The frequency of review and depth of the analysis will likely play an important role in the likelihood that the lender's assessment of credit risk will change. While the borrower might experience significant changes in financial performance, unless their situation is thoroughly reviewed or they experience a payment problem, their credit rating will likely remain unchanged.

The loan officer and the financial institution also take a long-term (multi-year) approach to assessment, and consider the current economic condition for the type of agricultural enterprise involved. Given the cyclical nature of agricultural prices, periodic "bad years" for any business are almost a certainty. Lenders will likely factor these cycles into their original risk rating and any subsequent changes, again limiting changes in a borrower's credit risk rating.

Judgment regarding non-financial variables also plays a key role in assigning and evaluating credit risk. Among other things, lender's make subjective assessments of the borrower's character, management capacity, and the future business prospects. While financial condition and performance are likely to change relatively quickly, non-financial factors are unlikely to undergo sudden or frequent changes. To the extent that non-financial factors are important in determining credit ratings, they will likely have a stabilizing affect on credit risk ratings. On the other hand, when the lender perceives a change in these factors they may cause credit risk ratings to undergo drastic or frequent changes.

The role of the loan officer in assigning credit risk ratings is likely to add additional stability to internal credit risk ratings over ratings based solely on current and historical financial conditions. The loan officer in charge of the borrower's account frequently plays an important role in establishing the internal credit risk rating assigned to a borrower. Often, this person will play a central role in determining whether the credit conditions associated with the borrower have changed. This creates the possibility that the loan officer will be reluctant to change his/her original assessment, because doing so may signal to superiors that a mistake was made in the original assignment. A downgrade also requires that the borrower receive greater monitoring attention and requires more of the loan officer's time and effort.

The purpose of this paper is to examine the extent, causes, and impacts of agricultural credit risk migration. The credit risk migration problem is approached using lender loan records gathered from four agricultural lenders. The data include the lender's internal credit score for each borrower at four annual points in time. The first step in the analysis is to standardize the credit risk rating systems across the lenders. After standardizing the internal rating systems, changes in borrower credit risk are examined and credit risk migration matrices are developed. Next, factors hypothesized to influence or predict changes in credit risk are related to observed changes in credit risk. Finally, the paper examines whether borrowers who have experienced changes in credit risk pay higher rates than borrowers with similar credit risk but no history of credit risk changes.

Previous Research

Although there have been few studies of agricultural loan credit migration, anticipating changes in credit risk is critical to a lender's financial performance. Lenders incur

substantial costs monitoring credit risk. The loan servicing costs associated with high risk borrowers have been estimated at nearly 100 basis points (Gloy, Gunderson, and LaDue). If changes in a borrower's credit risk are identified early, the lender can protect his/her interest, address the situation with the borrower's management, and perhaps avoid the costs associated with default. Anticipating credit risk changes also allows the lender to direct scarce monitoring resources to the loans that are the most likely to transition to a higher credit risk category.

Analyses of public bond data suggest credit ratings tend to exhibit drift (Bangia, Diebold, Kronimus, Schagen, and Schuermann; Fons; Lando and Skodeberg). The presence of drift is important because it implies that borrowers undergoing recent changes in credit risk (either improvements or deteriorations) are more likely to experience similar subsequent changes in credit risk than borrowers that have not experienced a recent change in credit quality. However, it is not clear if loan credit quality ratings also exhibit drift. If drift were to exist and lenders were aware of it, one would hypothesize that lenders would be particularly skeptical of recently downgraded credits. Consequently, borrowers that have experienced recent downgrades would be expected to pay higher rates than borrowers of similar credit quality that had not been recently downgraded. However, it remains an unanswered question as to whether borrowers experiencing recent changes in credit risk pay higher rates than borrowers of similar credit quality with stable credit histories.

Credit Risk Migration

Credit risk migration matrices describe the likelihood that an obligor, bond, or loan in one rating category will remain in that category or transition to another category in the next

period. Often the likelihood of remaining in the same rating category from time t to $t + 1$ is referred to as the retention probability, the probability of moving to a lower credit quality category is a credit downgrade, and moving to a higher credit quality a credit upgrade.

Several studies have been conducted on the credit ratings produced by Moody's and Standard & Poor's. For instance, Fons reports that for issues in the middle of the Moody's ratings scale, the likelihood of upgrading is roughly equal to the likelihood of downgrading and that retention rates tend to exhibit the highest probabilities in credit risk migration matrices. Nickell, Perraudin, and Varotto summarize the migration matrices presented in several studies. Retention rates for the highest rated credits (on Moody's scale) Aaa, Aa, and A are all greater than 90%, retention rates for Baa, Ba, and B are all greater than 80%, and retention rates for credits of quality Caa and lower are less than 70%.

Fons observes an apparent drift in rating changes, noting that upgrades are more likely to follow previous upgrades than either unchanged ratings or previous downgrades. Importantly Fons notes that firms undergoing recent downgrades are much more likely to experience a subsequent downgrade or default than firms that had not undergone a recent change or had experienced a recent upgrade.

The idea of credit rating drift in the Moody's and Standard & Poor's ratings was also examined by Lando and Skodeberg and Bangia, Diebold, Kronimus, Schagen, and Schuermann. These studies found that the previous credit risk rating category was important in estimating the likelihood that a credit would transition to another credit risk

category. Both found evidence that firms that have undergone downgrades (upgrades) seem to be more likely to experience further downgrades (upgrades).

The previous studies of credit migration and ratings drift focused on analysis of ratings produced by credit rating agencies such as Moody's and Standard & Poor's. Far fewer studies have been conducted on the ratings assigned to borrowers by a financial institution, or internal credit risk ratings. Internal credit risk ratings serve a variety of purposes including guiding loan origination, portfolio monitoring and reporting, analysis of adequacy of loan loss reserves, profitability and loan pricing analysis, and as inputs to portfolio risk models (Treacy and Carey).

The lack of analysis of internal credit ratings is not surprising. Carey and Hrycay point out that that few institutions have developed data sets that allow researchers to estimate default and loss experience for their internal rating systems. They suggest that in order to estimate default by internal credit rating category, financial institutions often map their ratings into external ratings systems such as Moody's or Standard & Poor's or rely on credit scoring models to estimate the likelihood of default.

Barry, Escalante, and Ellinger use a slightly different approach and estimate credit risk migration matrices from farm business summary data. They find that retention rates are the highest rates in the credit risk migration matrices, but that these retention rates are much lower than those estimated in studies utilizing rating agency data. This result could be a function of the characteristics of the financial performance of agricultural businesses and/or the different types of data used to estimate the matrices. As opposed to the "through-the-cycle" approach used by the rating agencies, theirs is based on the current and historical financial situation of the farm business.

The financial performance variability found in Barry, Escalante, and Ellinger's study is generally consistent with other studies of farm financial performance. For instance, Gloy, Hyde, and LaDue found evidence that profitability differences amongst farms tend to persist, such that the most profitable farms in any given year are likely to be the most profitable farms in subsequent years and the least profitable farms tend to be the least profitable in subsequent years. To the extent that profitability plays a role in credit ratings, this result would lead to similar conclusions as Barry, Escalante, and Ellinger. Specifically, one would expect that to find a tendency for credit ratings to remain constant over time, particularly for the highest and lowest credit ratings.

Data

Borrower level data were gathered from four agricultural lenders. The lenders represent both commercial banks and farm credit associations in the Northeastern United States. The lenders all have substantial agricultural loan portfolios, each with an agricultural loan portfolio approaching or exceeding \$100 million. In 2001, loan records for 670 borrowers were examined. Loan files were examined in order to identify the lender's current credit rating for each borrower and the credit rating assigned to the borrower in 2001, 2000, 1999, and 1998. In some cases the loan files did not contain credit ratings for previous years. For instance, the customer may have been recently added to the loan portfolio so the information was not available.

The loan files were also used to gather data regarding loan balances, types and terms of loan products, and interest paid by the borrower. In addition to extensive amounts of data gathered from each borrower's loan records, the borrower's loan officer completed a questionnaire designed to gather information regarding the borrowers

personal and business characteristics and the amount of time that various personnel spent with the borrower over the last 12 months.

Because most lenders' portfolios contain a large number of small, low risk loans, a stratified sampling approach was used when selecting borrowers for inclusion in the sample. Each lender's portfolio was stratified by size and risk. Then a random sample was selected from within each stratum. This resulted in the sample containing greater proportions of high risk and large loans than are present in the lenders' portfolios and insured that sufficient data were collected to analyze these types of borrowers.

Characterizing the Internal Risk Rating Systems

Regulators such as the Board of Governors of the Federal Reserve System (BOG) and the Office of the Comptroller of the Currency (OCC) divide asset quality into three general categories, pass, special mention, and adverse (Board of Governors of the Federal Reserve System and Office of the Comptroller of the Currency). As financial institution regulators, the BOG and the OCC are particularly concerned about the highest risk loans, those classified as adverse. Both regulators place adverse loans into substandard, doubtful, and loss categories. In general, these are loans on which the lender expects to take a loss of interest and/or principle or expects that the costs of securing and collecting their claims will be substantial.

Although the lenders in the sample represent commercial banks and Farm Credit System associations, their internal credit risk rating systems were similar. In order to make comparisons across lenders it was necessary to translate each lender's internal credit risk rating into a rating system that could be applied to all lenders. Each lender's risk rating system was translated into a five-tiered risk rating system. A five-tiered

system was chosen to provide the greatest amount of tiers that were comparable across lenders (Table 1).

The top three tiers of the risk rating system consist of pass quality loans. While the BOG and the OCC do not characterize the least risky loans beyond the pass categorization, all of the lenders in our sample used several categories to differentiate amongst pass quality loans. Some lenders used four categories to distinguish amongst the diversity of credit quality in pass loans, and other lenders used three. Consequently, when the lender had four categories of pass loans, two of the categories were merged so that the end result was three tiers of pass quality loans. The financial condition of borrowers in the top three tiers is relatively strong with solid financial conditions and repayment capacity that declines from tier one to tier three. The amount of monitoring also increases as one moves from tier one to tier three.

The special mention rating category became the fourth tier in the risk rating system. Each of the lenders used a risk rating category to identify loans in the regulatory category of special mention or OAEM (other assets especially mentioned). These borrowers require significant monitoring efforts and have significant weaknesses that threaten repayment capacity.

The fifth tier of the system contained all of the adverse quality loans. In general, there were very few loans in the adverse risk categories. Three of the financial institutions used a risk rating system that directly corresponded to the three adverse subcategories used by BOG and OCC. One lender used a more refined internal measure for adverse loans (4 categories of adverse loans) and one used a less refined internal measure, grouping all adverse loans into one category. Borrowers in tier five are

potentially past due on their debt payments and the lender is likely to take a loss on these loans.

Credit Risk Migration Matrices

Migration matrices were developed to describe the proportion of borrowers that arrived in a risk rating class in period t given their risk rating in period $t-k$. The entries of the credit risk migration matrix for year $t-k$ to year t are given by p_{ij} .

$$1) p_{ij} = \frac{n_{ij}}{N_i}$$

where n_{ij} is the number of borrowers transitioning from credit risk category i to j , and N_i is the number of borrowers in credit risk category i in period $t-k$. Under this formulation, the rows of the migration matrix sum to 1 and the entry in a given cell indicates the proportion of borrowers that began the period in tier i and ended in tier j .

When calculating the migration matrix, each of the observations was weighted for consistency with its proportion in the lenders' portfolios. This was necessary because the study design relied upon a stratified (size and risk) sampling approach when selecting borrowers for analysis. The data cover the years 1998 to 2001 so that it is possible to construct migration matrices that cover a variety of time periods. Results are presented for one, two, and three year migration matrices (Tables 2-4). The one and two year migration matrices include results from multiple time periods, while the three year migration matrix is the only matrix that can be estimated from the data. For instance, rather than presenting the three annual migration matrices (1998 to 1999, 1999 to 2000, and 2000 to 2001), the average annual migration matrix is presented (Table 2).

Across all time periods and risk classifications, internal credit risk ratings show a very strong tendency for retention. For instance, the retention rate for the lowest risk

borrowers ranged from 96.7% in the annual case (Table 2) to 90.1% in the three year case (Table 4). Of the lowest risk borrowers (tier one) experiencing a credit downgrade, the vast majority were downgraded one credit quality level to tier two and very small proportion transitioned to special mention (tier four).

Borrowers in the highest risk tier also showed a very strong tendency to remain in the highest risk category (94.7% in the annual migration case). The most likely migration from the high risk category was to the special mention category. Interestingly, for all time periods covered, the second greatest migration probability for high risk borrowers was to the lowest risk tier. While likelihood of an upgrade of this magnitude is quite low, 1.3% (Table 2) to 4% (Table 4), it is perhaps surprising that credit quality would undergo such an extreme transition. Such changes are likely the result of the restructuring of an adverse loan such as bringing on an additional guarantor that completely changes the credit risk of the situation.

The migration matrices indicate that for tiers two through four, there is a greater likelihood of downgrading than upgrading. The only substantial exception to this result is the case of tier four in the three year migration matrix, where the likelihood of an upgrade is 15.2% versus a 9.3% chance of transitioning to tier five. For tiers two and three, the likelihood of a downgrade is roughly double the likelihood of a credit risk upgrade regardless of the time period considered.

The matrices also demonstrate that the likelihood of transitioning to the highest risk category increases substantially as credit quality declines. For instance, it is extremely rare for a borrower in tier one or two to transition to the high risk category even over a three year period. On the other hand, the likelihood of a special mention

borrower (tier four) reaching adverse status (tier five) approaches 10% in the two to three year migration matrices.

The general tendency toward credit risk rating retention declines as credit risk increases until one reaches the highest risk category. For example, in the annual matrix the retention rate falls from 96.7% to 89.9% until climbing to 94.7% in the fifth tier. Both this result and the high likelihood of credit risk rating retention are consistent with and are similar in direction to the analyses of rating agency data summarized in Nickell, Perraudin, and Varotto. While the directional effects appear similar, the magnitudes of the retention probabilities in Tables 2-4 are slightly greater.

The estimates in Tables 2-4 indicate a much lower likelihood of changes in credit risk than those estimated by Barry, Escalante, and Ellinger. For instance, the retention estimates based on annual credit scores (Table 2 of Barry, Escalante, and Ellinger) showed a 75% retention rate for high quality borrowers, falling to 42%, 42%, 28%, and 35% for lower quality credits.

There are several important reasons that the estimates in Tables 2-4 differ from those in Barry, Escalante, and Ellinger's study of agricultural credit risk migration. The first is that although the issue of credit risk migration is central to both investigations, the estimates are based on considerably different data and different approaches to analyzing the relevant data. The estimates in Barry, Escalante, and Ellinger are based upon a historical analysis of very detailed farm business performance data, but with no non-financial information.

The estimates in Tables 2-4 are based upon lenders' analyses of often limited historical data and their perspective on how future conditions will impact credit quality.

The data in this study incorporate the significant impact that lender judgment has on credit risk assessment. Most lenders consider factors such as the borrower's character, track record with debt repayment, and collateral when evaluating credit risk. These factors are likely to be much less variable than farm business performance. The two data sets also represent different populations and result from a different selection process. FBFMA data are representative of all of the farms willing to participate in a business analysis program in the given region including non-borrowing farms and farms that utilize government credit sources, while the data in this study are likely more representative of the borrowers that would be found in a commercial lender's loan portfolio.

Barry, Escalante, and Ellinger's study provide excellent estimates of the extent to which farm economic performance and theoretical credit capacity vary over time. However, as they note it is difficult to model how lender judgment of financial factors and intangible elements such as character influence credit ratings. The internal ratings in this study also reflect the impact of the lender's assessment of future financial conditions. In this respect the estimates in Tables 2-4 are more representative of a "through-the-cycle" approach to credit risk than a "point-in-time" approach.

The data in this study represent a much shorter time frame. It is possible that were a longer period of time considered, economic cycles in the farm sector could influence the credit risk migration matrices estimated in Tables 2-4. However, the different cycle timing for various enterprises likely reduces the impact of cycles (except for the case of an industry-wide recession) and the value of historical data beyond 2 to 3

years (Novak and LaDue). Data limitations also make gathering longer time series both difficult and expensive.

Both approaches have merit when considering credit risk. Barry, Escalante, and Ellinger's approach provides a very detailed analysis of how farm business performance varies over time and how it influences factors related to credit risk. These factors should be among the most critical elements in determining credit risk. The approach used in this study highlights the importance that factors such as character, collateral, and judgment play in determining credit risk and how they interact with economic performance to establish the lender's view of credit risk. The estimates provided in this paper suggest that these factors have a substantial stabilizing impact on credit risk ratings.

Finally, several similar results emerge from the two studies. Both find that retention rates fall as credit quality declines, until reaching the highest risk borrowers. Similarly, both demonstrate that in most cases the likelihood of downgrading is greater than the likelihood of upgrading. Finally, the likelihood of reaching the highest risk classification for high quality borrowers is very small and this likelihood increases substantially as initial credit quality declines.

Explaining Credit Downgrades

Borrowers experiencing declines are of the greatest concern to lenders. An assessment of borrowers experiencing a change in credit risk over the 4 year period indicates that, consistent with the credit risk migration matrices, no change in credit risk was the most common occurrence, and credit risk downgrades were more prevalent than upgrades (Table 5). Of the borrowers with credit risk histories covering the 4 years, 84.7% experienced no change in credit risk, 5.3% experienced a credit risk upgrade, and 10.7%

were downgraded. A logistic regression model was developed to examine the factors that influence the likelihood of a credit risk downgrade.

$$(2) \text{ Prob}(\text{downgrade}|\mathbf{X}) = \frac{\exp(\boldsymbol{\beta}'\mathbf{X})}{1 + \exp(\boldsymbol{\beta}'\mathbf{X})} ,$$

where the probability of a credit quality downgrade is a function of a matrix of explanatory variables, \mathbf{X} , and $\boldsymbol{\beta}$ is a vector of parameters to be estimated. The model was estimated with unweighted sample data. The borrower's average daily loan balance was used to control for size. Indicator variables for the borrower's risk rating in 1998 were used to control for risk. Additional variables were included investigate the influence of a variety of borrower characteristics on the likelihood of a credit risk downgrade.

Nickell, Perraudin, and Varotto found that factors such as the business cycle and industry impact credit risk migration. To control for industry effects, indicator variables were included to identify whether the borrower's primary agricultural enterprise was dairy, annual crops, livestock other than dairy, permanent plantings, green (horticultural), or other (omitted). Because the collateral and cash flow characteristics of the various types of businesses are different, it is expected that borrowers in some industries may be more likely to experience downgrades. Similarly, different agricultural industries are likely to be in different stages of their industry economic cycle.

The model includes indicator variables identifying the lending institution in order to allow for the possibility that some lenders are more likely to downgrade borrowers than other lenders. A variable was included to describe the proportion of debt accounted for by lines of credit as opposed to longer-term mortgages. This variable is designed to capture the possibility that borrowers financed with operating lines of credit are subject to

greater variability in credit risk and may be more likely to be downgraded than a longer term mortgage borrower.

Finally, two sets of indicator variables were included to describe borrowers' business and personal characteristics. Loan officers were asked to identify each borrower's business as a beginning farmer, a growing business, a stable business, or a declining business. The characteristics of each stage were defined by a detailed set of instructions. A summary of the stages is provided in Table 6. The characteristics of these stages were generally defined to correspond to those described by Boehlje and Eidman's farm business lifecycle. The questionnaire provided an opportunity to distinguish transferring businesses from declining businesses, but these categories were combined for purposes of analysis. It is expected that other things equal, beginning and growing businesses will have the greatest chance of experiencing adverse financial outcomes and will have the greatest likelihood of a credit risk decline.

Loan officers were also asked whether the primary borrower was single, married without children, married with young children, married with college age children, in their "silver years" (actively involved in the management of the business but children are past college age), or in retirement. Data were also collected to identify borrowers that were divorced. For implementation in this model, several of the categories were aggregated so that the remaining categories were single, married (with or without children), silver years, or retirement. The impact of this variable on the likelihood of a credit risk downgrade is difficult to predict. As an individual passes through different life stages it is likely that their financial needs, desires, and risk tolerance will change. For instance, borrowers that are married or approaching retirement likely have greater cash flow needs and less

tolerance for risk than a single individual. Following this argument one would expect that single borrowers would be the most likely to experience a credit risk downgrade.

The model was estimated using data from borrowers with credit risk ratings that covered the entire four year period and that began the period with a credit rating better than the special mention category (tier four). The choice to exclude borrowers beginning in the special mention category was made because few lenders would desire to make a new loan to a borrower in this category. Likewise, a downgrade from special mention to adverse is a special type of downgrade that should likely be treated differently than a downgrade from tier one to tier two. The parameter estimates for the model and the associated marginal effects calculated at the means of the explanatory variables are shown in Table 7. Because the model is non-linear, the marginal effects change as the levels of the variables change.

The model fit is reasonable, but not outstanding, particularly if one considers its success in classifying borrowers that did and did not experience a credit downgrade over the period (Table 8). The model correctly predicted 34 of the 101 borrowers that experienced a credit risk downgrade over the four year period. Slightly over half of the downgrade predictions were correct.

The significance of the group of indicator variables for the lending institution indicates that the likelihood of a downgrade varied by lender, with lender two having a higher likelihood of downgrading borrowers. Because the model controls for borrower size, risk, and industry types one can conclude that the lender effect is likely due to institutional differences in how credit quality is analyzed and evaluated. Lenders two and three had the greatest differences in the likelihood of downgrading.

The likelihood of a credit downgrade nearly doubles as the initial risk level of credit risk increases. The explanatory variables for risk rating tier indicate that other things equal, borrowers that were in tier three in 1998 had a 20% greater chance of experiencing a downgrade than did borrowers who were in credit risk tier one in 1998. As opposed to the data in the credit risk migration matrices this is a relatively pure risk effect. Likewise, the effects were estimated using only data from borrowers that began the period with credit quality greater than special mention (tier 4).

The personal and business stage indicator variables show some promise in identifying borrowers that are likely to experience credit downgrades. Borrowers that managed what loan officers identified as a declining business were by far more likely to experience a credit risk downgrade. Borrowers in the beginning, growth, or stable (omitted from model) stages all have similar likelihoods of experiencing a downgrade.

As expected, the personal stage variables indicate that older borrowers tend to have a lower likelihood of credit risk downgrades. The size of the marginal effects is quite large and would indicate that the effect is similar in magnitude to the risk effect described earlier. It is likely that these borrowers are operating more established businesses and probably take less relative risk than some of their younger peers.

The borrower's primary agricultural industry does not have a substantial impact on the likelihood of a credit risk downgrade. This is not to say that some industries are not more or less risky. The overall level of risk is accounted for by the risk tier. However, once risk tier has been established, it does not appear agricultural enterprise contributes to the likelihood of a credit risk downgrade at meaningful levels of statistical significance.

Interest Rate Margin and Credit Risk Migration

To the degree that lenders perceive drift in credit ratings, they could be expected to charge recently downgraded borrowers an interest rate premium over borrowers with similar credit risk ratings and stable credit histories. This additional risk premium should be reflected in the lender's interest rate margin. Although a borrower's current risk rating reflects their current credit risk, the presence of drift in credit ratings could influence loan pricing. If drift exists, borrowers with stable credit histories are less likely to experience credit risk downgrades than a borrower that has been recently downgraded.

The interest rate margin for each borrower was defined as the amount by which interest received on the loan exceeded the lender's cost of funds. Because a financial institution's cost of funds is difficult to estimate, the one-month certificate of deposit rate was used as a benchmark for the cost of funds. Although each institution will have a higher cost of funds than the CD rate, the cost of funds should move with the CD rate. The regression model was specified according to (3).

$$(3) \quad M = \beta_0 + \beta_1 \text{downgrade} + \beta_2 ADB + \beta_3 ADB^2 + \sum_{i=4}^6 \beta_i L_{i-3} + \sum_{i=7}^9 \beta_i \text{tier}_{i-6} + \beta_{10} \text{Term} \\ + \beta_{11} \text{LOC} + \beta_{12} \text{Fixed} + \varepsilon$$

Where M is the interest rate margin in basis points (3% was recorded as 300), downgrade is an indicator variable for borrowers that experienced a credit risk downgrade over the four year period of 1998-2001, ADB is the average daily loan balance measured in dollars, L is an indicator variable for the lender, tier is an indicator variable for risk tier in 2001, Term is the weighted average of the term remaining on the debt measured in years, LOC is the percent of ABD in lines of credit measured percentage points (10% was

recorded as 10), *Fixed* is the percent of ADB with fixed rates measured in percentage points, the β 's are parameters to be estimated, and ε is a normally distributed error term.

The model is designed to test the hypothesis that a credit risk downgrade in the borrower's history does not influence interest rate margin. In order to accurately test this hypothesis, it is critical to control for loan volume and current risk levels. Because lenders likely have different views about the appropriate magnitude of credit risk premiums, indicator variables are included to capture lender pricing impacts. The weighted average term remaining on a borrower's outstanding loans was included to capture the possibility that borrowers with longer term loans may have different rate structures. Similarly, the proportion of debt in lines of credit is included as a control because lines of credit are reviewed on a yearly basis and may have different margin structures. The cost of funds for each fixed rate loan was recorded based on information provided by the financial institution resulting in a constant interest rate margin through time on each particular fixed rate obligation. However, this margin may be greater or lower than the margin on variable rate commitments.

The parameter estimates for the interest rate margin model are shown in Table 9. The model explains interest rate margin relatively well with an R-Square over 50%. The impact of loan volume on interest rate margin is significant. The negative sign on the ADB term and the positive sign on the squared ADB term indicate that interest rate margin initially declines with loan volume, but reaches a minimum and then begins to increase as loan volume increases.

The set of lender indicator variables highlight the wide differences in loan pricing used by the various financial institutions. The risk premium charged for tier two as

opposed to tier one risk levels was nearly 33 basis points. According to their pricing, the lenders tended to view changes from tier one to tier two and from tier three to tier four as the most important changes in risk. The premium for moving from tier two to tier three was 18.61 basis points and the premium for moving from tier three to tier four was another 32 basis points.

The variables for term remaining and the use of lines of credit also had statistically significant impacts on loan pricing. As term increased the average interest rate margin declined although the magnitude of the decline was relatively small. The proportion of debt accounted for by lines of credit also had a relatively small impact on loan pricing. If the proportion of loan volume financed with lines of credit were to increase by 10 percentage points, interest rate margin would decrease by nearly 5 basis points.

The model did not produce enough evidence to reject the hypothesis that borrowers with a history of credit risk downgrades paid the same rates as borrowers with similar credit ratings and stable credit histories. The modest evidence that is presented would suggest that borrowers with a recent downgrade in their past may actually pay more favorable rates than their higher risk peers. This would be possible if the lender felt that the borrower was at the top of their new credit risk class but not of high enough quality to remain in their previous, lower risk class. The result could also reflect an unwillingness to significantly alter the borrower's rate. Instead, the changes in risk class could bring additional monitoring efforts.

The results indicate that lenders do not charge borrowers with unstable credit histories higher rates than borrowers with similar current credit ratings and stable credit

histories. Several possibilities would explain this result. First, drift may not be present in agricultural loan portfolios. Alternatively, drift may be present but lenders are not aware of its presence. It is possible that lenders may be aware of drift, but do not feel that it is economically important. Finally, competition may work to remove the pricing associated with drift.

If a downgrade of a low risk borrower occurs, the borrower could likely find an alternate source of credit. The alternate lender would rate the current level of credit risk in a fashion similar to the previous lender, but would have limited knowledge about how the borrower's credit risk had transitioned over time. In this way, it is possible that a history of the borrower's credit risk is a source of information that has little benefit to the lender other than to assist them in the decision of whether to make additional extensions of credit at the prevailing rate for borrowers with similar credit risk.

Summary

This study examined the extent, causes, and impacts of agricultural credit risk migration. The credit risk ratings assigned to 670 borrowers were gathered from agricultural lenders covering the period of 1998 to 2001. Each lender's credit risk rating system was mapped into a five-tiered risk rating system in order to compare the ratings across lenders.

The ratings were used to develop credit risk migration matrices. The matrices demonstrated a strong tendency for borrowers to remain in their current credit risk class. This tendency was substantially greater than in the credit risk migration matrices estimated from farm record data by Barry, Escalante, and Ellinger.

In most cases, the likelihood of experiencing a credit risk downgrade was greater than the likelihood of a credit risk upgrade. It is apparent that the likelihood of

transitioning to the adverse credit category (tier five) increases considerably as credit risk increases. The likelihood of transitioning directly from the lowest risk category to highest risk category was nearly zero. On the other hand, the chances of transitioning from the special mention (tier four) of the risk rating system to the adverse category (tier five) ranged from 5% to 10% depending on the time period considered.

In general, the results in this study indicate that lender risk ratings are more stable than ratings based on credit scores estimated from financial statements. The results highlight the importance that non-financial factors plays in assessing credit risk. When assessing credit risk the lender must account for factors such as management capacity, character, and collateral in addition to financial conditions. The judgment of these factors produces credit risk ratings that are much more stable than ratings produced only from variables constructed from financial statements. Because these non-financial statement factors play such an important role in stabilizing credit risk, additional work is needed to understand the factors that lenders consider and how these factors contribute to their assessment.

This study takes a first step in examining how internal credit risk ratings transition over time. Additional data with a longer time horizon is needed to more completely assess migration. One of the most important issues related to credit risk is developing an understanding how internal credit risk ratings relate to actual loan losses. In order to make this assessment additional data and work is needed to estimate economic losses generated by high risk and default loans.

Logistic regression was used to examine the role that several factors played in predicting a credit quality downgrade. Factors such as the borrower's personal

characteristics and the stage of the business life-cycle provided useful information in predicting downgrades. Borrowers that were actively involved with the business but with children past college and borrowers that were in the process of retiring were the least likely to experience a credit risk downgrade. Among the business stages, borrowers with businesses that were identified as in the decline or disinvestment stage were by far the most likely to experience a credit risk downgrade. The type of primary agricultural enterprise did not have a meaningful impact on the likelihood of downgrades.

The history of a credit quality downgrade did not appear to influence a borrower's interest rate relative to borrowers with similar current credit risk and no history of downgrades. Because credit risk drift is the tendency for downgrades to be followed by subsequent downgrades, this result would suggest lenders do not feel that drift is meaningful enough to price, are not aware of drift in their ratings, or that they do not experience drift in their ratings.

Table 1. Description of the Standardized 5-Tiered Risk Rating System^a.

Level	Description
1	<ul style="list-style-type: none"> • Highest quality credits • Strong financial statements with high levels of profitability, liquidity, and repayment capacity • Very low likelihood of loss in the event of adverse industry financial conditions
2	<ul style="list-style-type: none"> • Strong credits • Financial statements with acceptable levels of profitability, liquidity, and repayment capacity • Strong repayment record • Low likelihood of loss in the event of adverse industry financial conditions
3	<ul style="list-style-type: none"> • Average quality credits • Financial statements are strong enough to justify extension of credit • History of timely repayment • Monitored frequently for compliance with covenants • Modest likelihood of default in the event of adverse financial conditions
4	<ul style="list-style-type: none"> • Classified as special mention or OAEM • Highly leveraged and the financial statements reveal several weaknesses that threaten repayment. • Require substantial attention • Uncorrected weaknesses may seriously threaten repayment capacity. • Currently experiencing adverse economic conditions or if experienced repayment could be jeopardized • Collateral securing the loan may be questionable • Although possible, default is not imminent
5	<ul style="list-style-type: none"> • Classified, substandard, doubtful, or loss • Inadequate collateral and repayment capacity. • The likelihood of loss of interest and principal is high or the lender must go to great lengths to protect their position • All loans for which interest and principle are in excess of 90 days past due or classified as non-accrual. • Repayment likely depends upon collateral.

^a The descriptions in this table, particularly for the regulatory classifications (4 and 5), draw heavily on the descriptions provided in the Comptroller's Handbook (pages 16-18).

Table 2. Average One-Period Risk Migration Matrix^a.

		Period 2 Risk Rating				
		1	2	3	4	5
		-----% of Borrowers -----				
Period 1 Risk Rating	1	96.7	3.1	0.0	0.2	0.0
	2	2.0	93.5	2.0	2.3	0.2
	3	0.6	1.4	93.6	2.5	1.9
	4	0.0	1.1	3.6	89.9	5.4
	5	1.3	0.1	0.6	3.3	94.7

^aPopulation estimates based upon 1,815 borrowers. The periods covered are 1998 to 1999, 1999 to 2000, and 2000 to 2001.

Table 3. Average Two-Period Risk Migration Matrix^a.

		Period 3 Risk Rating				
		1	2	3	4	5
		-----% of Borrowers -----				
Period 1 Risk Rating	1	94.0	5.5	0.2	0.3	0
	2	3.7	88.1	3.5	4.0	0.7
	3	1.0	3.7	86.2	4.1	5.0
	4	0.0	1.7	9.1	79.1	10.1
	5	2.0	0.2	0.9	8.1	88.8

^aPopulation estimates based upon 1,145 borrowers. The periods covered are 1998 to 2000 and 1999 to 2001.

Table 4. Credit Risk Migration Matrix for 1998 to 2001^a.

		2001 Risk Rating				
		1	2	3	4	5
		-----% of Borrowers -----				
1998 Risk Rating	1	90.1	8.9	0.3	0.7	0
	2	5.2	83.5	4.4	5.8	1.1
	3	2.1	2.9	82.9	4.6	7.5
	4	0	3.5	11.7	75.5	9.3
	5	4.0	0	1.4	9.3	85.3

^aPopulation estimates based upon 555 borrowers.

Table 5. Proportion of Borrowers with Changes in Credit Risk Over a 4 Year period^a.

Risk Rating	Percent of Portfolio ^b
No Change in Credit Risk	84.7%
Experienced Change in Credit Risk	15.3%
Upgraded	5.3%
Downgraded	10.5%

^aPopulation estimate based upon 555 observations.

^bThe total of upgraded and downgraded does not equate to the total experiencing a change in credit risk because a small number of borrowers experienced both an upgrade and a downgrade.

Table 6. Description of the Borrower Business Stages.

Stage	Description
Beginning Farmer	A business that has been recently established. This would include a person who just started farming on a full or part-time basis or recently switched from a part-time to an approximately full-time farm. A person in this stage is still dealing with the issues and problems of business establishment.
Growth	A business that is in the expansion or growth phase of the business. Expansion of the business is a part of the plan of the operator(s). They may have expanded within the last few years or are planning to expand within the next few years. They may be operating in a manner to gradually expand their business
Stable	A business in which the operator has achieved the maximum size that (s)he desires or believes to be achievable. While modest growth or decline in the size of the business may take place over time, it is not the intent of the management to increase (or decrease) the size of the business.
Decline or Disinvestment	A business that is in the process of being transferred or a business that is declining in either size or aggressiveness of the manager. The manager may be reducing the size by renting less land or custom hiring functions. The business may be stagnating or atrophying. The operator may be “hanging on” until retirement or sale of the farm.

Table 7. Parameter Estimates for Credit Risk Downgrade Model.

Parameter	Estimate	Marginal Effects	Wald Chi-Square Statistic
Intercept	-1.3172		3.31*
ADB	1.3E-06	0.0000	8.63**
ADB ²	-1E-13	0.0000	3.97**
Lender 1	0.0306	0.0051	0.01
Lender 2	0.82349	0.1384	4.05**
Lender 3	-0.5802	-0.0975	1.53
Wald Chi-Square Statistic for LRT of Lender Group: 10.54**			
Tier 2 Risk	0.68251	0.1147	4.06**
Tier 3 Risk	1.23654	0.2079	8.40**
Wald Chi-Square Statistic for LRT of Risk Group: 8.75**			
Percent of Debt in Lines of Credit			
Beginning Farmer	-0.403	-0.0677	0.19
Growth Business	-0.4047	-0.0680	1.15
Declining Business	1.71936	0.2891	19.50**
Wald Chi-Square Statistic for LRT of Business Stage Group: 23.79**			
Single Borrower	-0.0219	-0.0037	0.00
Silver Year Borrower	-0.7005	-0.1178	3.65*
Retirement	-1.7152	-0.2883	4.00**
Wald Chi-Square Statistic for LRT of Personal Stage Group: 6.42*			
Dairy	-0.6097	-0.1025	1.04
Annual Crops	-0.3512	-0.0590	0.33
Other Livestock	-1.3111	-0.2204	2.61
Perm. Plantings	0.09237	0.0155	0.01
Green Industry	-1.1701	-0.1967	1.74
Wald Chi-Square Statistic for LRT of Industry Group: 5.18			
Likelihood Ratio Test Statistic for Model Significance: 75.35**			
Percent Classified Correctly: 72%			
Chi-Square statistic for Hosmer and Lemeshow Goodness of Fit Test: 4.62			
N= 330			

Table 8. Actual and Predicted Credit Risk Downgrades.

		Actual		Total
		No Change	Downgrade	
Predicted	No Change	202	67	269
	Downgrade	27	34	61
	Total	229	101	

Table 9. Parameter Estimates for Earned Interest Rate Margin in Basis Points.

Parameter	Estimate	t – statistic
Intercept	270.62	9.86**
Previous Downgrade	-22.89	-1.15
ADB	-9.25E-05	-4.31**
ADB ²	1.23E-11	3.65**
Lender 1	88.40	4.48**
Lender 2	178.42	8.17**
Lender 3	358.68	15.45**
F-Statistic for Lender Group: 90.39**		
Tier 2 Risk	32.94	1.74*
Tier 3 Risk	51.55	2.04**
Tier 4 Risk	84.29	4.05**
F-Statistic for Risk Group: 5.68**		
Average Remaining Term on Debt	-2.75	-1.88*
Percent of Debt in Lines of Credit	-0.48	-2.06**
Percent of Debt with Fixed Rates	-0.02	-0.05
F-Statistic for joint significance of parameters		
	33.91**	
R-Square	0.53	
Adjusted R-Square	0.52	
N= 372		

*indicates significance at the 0.10 level

**indicates significance at the 0.05 level

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