Credit Risk Migration and Downgrades Experienced By Agricultural Lenders

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ABSTRACT: Agricultural credit risk migration is examined using loan records gathered from four agricultural lenders. Results indicate that lender risk ratings are much more stable than ratings based on credit scores estimated from financial statements, highlighting the importance that non-financial factors such as management capacity, character, and collateral play in assessing credit risk. Additionally, the borrower's risk tier, personal characteristics, and the stage of the business life-cycle provide useful information in predicting credit quality downgrades, while the primary agricultural enterprise does not impact the likelihood of a downgrade.

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

Credit Risk Migration and Downgrades Experienced By Agricultural Lenders

Predicting changes in portfolio credit risk is often based on the credit risk migration of individual loans. The topic of credit risk migration 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 (Lando and Skodeberg; Bangia, et al.; Oderda, Dacorogna, and Jung; Crouhy, Galai, and Mark; Nickell, Perraudin, and Varotto; Fons; Carey and Hrycay). With respect to agricultural lending, the proprietary nature of loan data, small portfolios, and the tendency for lenders to change their rating systems has limited the number of studies that report transitions of loan quality ratings.

Studies of agricultural credit risk migration have often been based on credit scores estimated from farm business financial records. Because lenders consider both financial and non-financial factors as well as a borrower's future business prospects, there is good reason to believe that lender credit risk ratings will differ from ratings based on estimated credit scores. The lack of connection between actual practice and previous academic studies makes it important to examine the issue of credit risk migration using actual lender risk ratings. The results will help explain how credit risk transitions over time and factors that might contribute to changes in credit risk.

The purpose of this study is to examine the extent and causes of agricultural credit risk migration in the portfolios of four agricultural lenders operating in the Northeastern U.S. The study is one of the first to use internal lender credit ratings to examine the credit risk migration of agricultural loans. The data include the lender's internal credit rating for each borrower at four annual points in time. This approach overcomes one of the main obstacles to the study of credit risk migration, the proprietary nature of borrower data.

Although the data come from institutions in the Northeastern U.S., they are regulated by national regulatory agencies, and there is little reason to believe that the risk rating processes and standards employed by these institutions are fundamentally inconsistent with risk rating systems and processes used by lenders in other regions. The time, cost, and confidentiality of the data collected also limited the number of lenders from whom such data could be collected. In order to overcome sample size issues, data on a large number of borrowers from these lenders were gathered.

Previous Research

Barry, Escalante, and Ellinger used farm record keeping association data to examine credit risk migration. Using financial performance data from a large number of Illinois farms over the period of 1985-1998, they calculated credit scores for the farms and developed migration matrices that describe how the scores changed over time. While this approach is reasonable, it is not clear how closely credit ratings estimated from farm financial performance correspond to the internal credit ratings assigned by agricultural lenders. Many factors make it unlikely that internal credit risk ratings will exhibit as much variability as those estimated from farm financial data.

When originating a loan, the lender decides whether the borrower represents an acceptable credit risk. In this process the lender balances the costs of loan misclassification associated with Type I and II errors (LaDue; Nayak and Turvey). In some cases this judgment 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, some borrowers may be subject to more frequent and thorough reviews than others. The frequency of review and depth of the analysis may 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 reviewed or they experience a payment problem, their credit rating may remain unchanged.

In a study designed to identify important variables for credit risk rating models, Zech and Pederson conclude that it is important to separately consider farm financial performance and repayment capacity. This approach is consistent with the loan officer and the financial institution taking a long-term (multi-year) approach to assessment in which they 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 likely factor these cycles into their original risk rating and any subsequent 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, lenders make subjective assessments of the borrower's character, commitment to repay, management capacity, and future business prospects. In a small sample of North Dakota lenders, Gustafson, Beyer, and Saxowsky found that lenders viewed honest and integrity as two of the most important subjective borrower characteristics.

The lender's assessment of subjective borrower characteristics such as character plays an important role in the credit risk evaluation process, but their impacts are difficult to quantify (Gustafson). While financial condition and performance are likely to change relatively quickly, non-financial factors such as character and management capacity are unlikely to undergo sudden or frequent changes. To the extent that non-financial factors are important in determining credit ratings, they likely have a stabilizing impact on credit risk ratings. On the other hand, when the lender perceives a change in these factors, credit risk ratings may undergo substantial changes.

Because the loan officer plays a key role in assigning credit risk ratings it is likely that the ratings will be more stable than ratings based solely on current and historical financial conditions. Often, the loan officer's judgment plays a central role in determining whether the credit conditions associated with the borrower have changed. These factors create 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 assessment. A downgrade also requires that the borrower receive greater monitoring attention and requires more of the loan officer's time and effort.

Although there have been few studies of credit risk migration for agricultural loans, 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 greater than those associated with low risk borrowers (Gloy, Gunderson, and LaDue). If changes in borrowers' credit risk are accurately identified, the lender can reduce 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.

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 a subsequent period. Often, the likelihood of remaining in the same rating category from time t to $t + 1$ is referred to as the retention probability, while the probability of moving to a lower credit quality category is termed 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 Moody's ratings scale, the likelihood of upgrading is roughly equal to the likelihood of downgrading, and that retention probabilities are often the highest probabilities in credit risk migration matrices. Nickell, Perraudin, and Varotto report that the highest rated credits (on Moody's scale) Aaa, Aa, and A exhibit annual retention rates greater than 90%, Baa, Ba, and B exhibit retention rates greater than 80%, and that retention rates for credits of quality Caa and lower are less than 70%.

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, analysis of adequacy of loan loss reserves, 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 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. The mapping approach is likely problematic in agricultural lending because in addition to obvious industry differences, agricultural businesses and loans are typically much smaller than those followed by the rating agencies.

Barry, Escalante, and Ellinger use a slightly different approach and estimate credit scores and 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. Their results could be due to 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 to find a tendency for credit ratings to remain constant over time, particularly for the highest and lowest credit ratings.

Data

Historical internal credit risk ratings and additional 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 589 borrowers were examined as part of the credit risk component of a larger research project (LaDue, Gloy, and Cuykendall; Gloy, Gunderson, and LaDue). Because most lenders' portfolios contain a large number of small, low risk relationships, a stratified sampling approach was used in order to obtain adequate data on larger and riskier lending relationships. Each lender's portfolio was stratified by three size and three risk categories. Then, a random sample of borrowers was selected from within each stratum (Table 1). Relationships, not individual loans, were sampled. A loan relationship was defined to include all the loans and people associated with a single business.

The risk categories ranged from borrowers that represented the lowest credit risks to borrowers in the highest credit risk categories. Those in the high risk category were defined as borrowers whose debts were no longer accruing interest or those for which the lender had taken a write-off of principal and interest obligations. Borrowers in the highest risk category were at least 90 days past due on their interest and principal obligations for at least one loan, and many had experienced loan write-offs within the past year.

The majority of the data was collected from lender computer and paper loan files. Specifically, 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, and as a result, historical credit risk 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.

Some data necessary for the study were obtained from a questionnaire completed by the loan officer responsible for the lending relationship. The questionnaire was designed to gather information regarding borrowers' personal and business characteristics and the amount of time that various personnel spent with borrowers over the prior 12 months.

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. As 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. For loans in these categories, the lender expects to take a loss of interest and/or principal, 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 to provide a scheme that could be applied across lenders (Table 2).

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 using four and others three. Consequently, when the lender had four categories of pass loans, two categories were merged to result in 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 a borrower 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 borrowers with adversely classified loans. In general, there were very few lending relationships in the adverse risk categories. Three of the financial institutions used risk rating systems that directly correspond 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 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}.

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

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. Weighting 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 intervals. At most, each borrower has a credit risk rating for each year from 1998 to 2001. Because some borrowers entered the lender's portfolio after 1998, the number of borrowers covered by a time period increases through time. For example, the number of borrowers with data for the period 1998-1999 is 521, the number for 1999-2000 is 551, and the number is 576 for 2000 to 2001.

As measured by the average farm financial conditions in New York State, the average net cash income, rate of return on assets, and debt repayment capacity increased considerably over the period (Table 3). Although these measures are not perfect indicators of the economic conditions in other states and the state average aggregate across all types of farms, it appears that the time period was generally favorable to farm financial performance.

Results are presented for one-, two-, and three-year migration matrices (Tables 4-6). 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, the three annual migration matrices (1998 to 1999, 1999 to 2000, and 2000 to 2001), are presented in Table 4. The individual probabilities in the table are the likelihood that a borrower in row *i* transitioned to column *j*. The row and column totals report the total proportion of borrowers in each row or column in any given year.

Across all time periods and risk classifications, internal credit risk ratings exhibit high retention rates.[1] For instance, the retention rate for the lowest risk borrowers ranged from 98.6% to 93.8% in the annual case (Table 4) to 88.9% in the three year case (Table 6). Of the lowest risk borrowers (tier one) experiencing a credit downgrade, the vast majority were downgraded one credit quality level to tier two and a very small proportion transitioned to special mention (tier four). Nearly 33 percent of the institutions' borrowers ended the period in tier one (Table 4).

Borrowers in the highest risk tier also showed a very strong tendency to remain in the highest risk category (91.4% to 96.5% in the annual migration cases). Roughly 7 percent of the borrowers were placed in this category. It is important to point out that these results represent borrowers, not loan volume. Migration from the highest risk tier was most often to the special mention category. For example, from 1999 to 2000, 8% of the borrowers in tier four transitioned to tier five (Table 4). Interestingly, there was a relatively large migration probability (3.8%) for high risk borrowers to the lowest risk tier in 2000 to 2001. While likelihood of an upgrade of this magnitude is quite low, 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 migration matrices starting from 1998. For example, in the 1998 to 2001 migration matrix the likelihood of an upgrade from tier four is 17.7% versus a 10.7% chance of downgrading to tier five. For tiers two and three, the likelihood of a downgrade is substantially greater than the likelihood of an 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 tier five. The greatest probability of transitioning from tier one or tier two to tier five is 1.3% which occurs for tier two borrowers in the three year matrix (Table 6). On the other hand, the likelihood of a special mention borrower (tier four) reaching adverse status (tier five) is typically 8% to 10%

The general tendency toward credit risk rating retention declines as credit risk increases until a relationship reaches the highest risk category. In the 1999-2001 matrix the retention rate falls from 90.9% in tier 1 to 76.7% in tier 4 until climbing to 87.8% 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 4-6 are slightly greater.

The results in Tables 2-4 indicate a much lower likelihood of changes in credit risk than those estimated by Barry, Escalante, and Ellinger who found a 75% retention rate for high quality borrowers, falling to 42%, 42%, 28%, and 35% for lower quality credits. There are several potential explanations for these differences.

Lenders form credit risk ratings on the basis of limited historical data and their perspective on how future conditions will impact credit quality. The results 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 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 4-6 are more representative of a "through-the-cycle" approach to credit risk than a "point-in-time" approach.

It is possible that were a longer time period considered, economic cycles in the farm sector could influence the credit risk migration matrices estimated in Tables 4-6. However, the different cycle timing for various enterprises likely reduces the impact of cycles on the portfolio (except for the case of an industry-wide recession) and the value of historical data beyond 2 to 3 years decays rapidly (Novak and LaDue).

Explaining Credit Downgrades

Table 7 reports the population estimates as well as the proportion of the sample that underwent changes in credit risk over the 4 year period of the study. Consistent with the credit risk migration matrices, no change in credit risk was the most common occurrence, and credit quality downgrades were more prevalent than upgrades. The population estimates suggest that over a 4 year period the vast majority (83.9%) of the relationships in the portfolio experienced no change in credit risk, 4.8% were upgraded, and 11.8% were downgraded. The data also indicate that it is rare for a borrower to be upgraded or downgraded more than one credit quality category.

A logistic regression model was developed to examine the factors that influence the likelihood of a credit quality downgrade over the period 1998 to 2001.[2]

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

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. Because controls for size and risk are included, the model was estimated with unweighted sample data. This approach does not produce estimates of the population model. Estimating the population model would reduce the impact of size and risk. In other words, weighting by relationship will emphasize the small/low risk loans that are more prominent in a lender's portfolio. Instead, the borrower's average daily loan balance was used to control for size and indicator variables for the borrower's 1998 risk rating were used to control for initial credit risk level. 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. Additional variables were included to investigate the influence of a variety of borrower characteristics on the likelihood of a credit quality downgrade. These characteristics included the primary agricultural enterprise, the lending institution that made the loan, the borrower's business stage, and personal stage. The expected impact of these variables is described below.

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.

Two sets of indicator variables were included to describe borrowers' business stage and personal characteristics. As part of the questionnaire that loan officers completed for each lending relationship, they were asked to identify each borrower's business stage as a beginning farmer, a growing business, a stable business, or a disinvesting/declining business. The characteristics of each stage were defined by a detailed set of instructions given to the loan officers. The business stages were generally defined to correspond to those described by Boehlje and Eidman's farm business lifecycle (Table 8). The questionnaire provided an opportunity to distinguish transferring businesses from disinvesting/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.

Finally, a set of indicator variables was included to describe borrowers' personal characteristics. Loan officers were 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. For implementation the categories were aggregated into single, married (with or without children), silver years, or retirement.

The expected impact of the personal stage variables on the likelihood of a credit quality downgrade is unclear. 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. If this is true one would expect that single borrowers would be the most likely to experience a 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 adverse category (tier five). Excluding these borrowers and those with missing data for explanatory variables resulted in 411 observations. The parameter estimates for the model and the associated marginal effects calculated at the means of the explanatory variables are shown in Table 9. 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 if one considers its success in classifying borrowers that did and did not experience a downgrade over the period (Table 10). The model correctly predicted only 37 of the 117 borrowers that experienced a credit quality downgrade over the four year period.

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 borrower's initial risk tier is one of the best predictors of whether a borrower will experience a downgrade. Reinforcing the conclusions drawn from the migration matrices, the likelihood of a downgrade increases rapidly as credit risk increases beyond tier one. The explanatory variables for risk rating tier indicate that other things equal, borrowers that were in tier two in 1998 had a 12.56% greater chance of experiencing a downgrade than did borrowers who were in credit risk tier one in 1998 and borrowers in tier three were nearly 26% more likely to downgrade than those in tier one. As opposed to the data in the credit risk migration matrices, this result is a relatively pure risk effect. Borrowers in tier four were not more likely to experience a downgrade than those in tier one (the omitted group). This result reflects the fact that similar proportions of borrowers in tiers one and four experienced downgrades. However, those in tier four can only downgrade to tier five which has additional regulatory implications, while a downgrade from tier one to tier two, or three is primarily for the lender's managerial purposes.

The personal and business stage indicator variables show some promise in identifying borrowers that are likely to experience downgrades. The significance of these variables highlights the importance of the lender's judgment over non-financial factors when assigning credit risk. Borrowers that managed businesses in the disinvesting/declining business stage were by far more likely to experience a downgrade.[3] Borrowers in the beginning, growth, or stable (omitted from model) stages all had similar likelihoods of experiencing a downgrade.

As expected, the personal stage variables indicate that older borrowers tend to have a lower likelihood of credit quality downgrades. The size of the marginal effect 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 peers with less established businesses.

As a group, the borrower's primary agricultural industry did 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. However, once risk tier has been established, it did not appear agricultural enterprise contributes to the likelihood of a credit risk downgrade at meaningful levels of statistical significance.

Summary

The credit risk ratings assigned to 589 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 found 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 quality downgrade was greater than the likelihood of a credit quality 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 category (tier four) of the risk rating system to the adverse category (tier five) ranged from 1% to 14% 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, commitment to repay, 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 and how these factors influence repayment.

Additional data with a longer time horizon are needed to more completely assess migration. One of the most important issues related to credit risk is developing an understanding of how internal credit risk ratings relate to actual loan losses. In order to make this assessment additional data and work are 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. Initial risk tier was among the most important determinants of the likelihood of experiencing a downgrade. As credit risk increased the likelihood of a downgrade increased until the borrower reached tier four. 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. Finally, the type of primary agricultural enterprise did not have a meaningful impact on the likelihood of downgrades.

Notes:

1. The lenders in the study do not necessarily re-rate all of their loans. While the situation of most loans is evaluated each year, it is possible that some performing loans remain in their current category simply because their situation is not thoroughly evaluated. It is difficult to accurately estimate the number of relationships that fall into this situation, but one would expect that it should be relatively small. The lender has an incentive to accurately assess credit risk deterioration and the borrower has an incentive to encourage the lender to accurately assess credit risk improvement.

2. Although it is technically possible to estimate a model that explains upgrades as well as downgrades, there were relatively few upgrades experienced in the sample. Experimentation with a simple logit model for upgrades and found no

statistically significant parameters. This result limited the interpretive power that might be gained by estimating an ordered logit model. Models that would examine downgrade severity or the number of years in a cell was also beyond the data as most downgrade/year cells would contain a very limited number of borrowers.

3. Because the lender's opinion was used to identify businesses that are in decline it is possible that this relationship is endogenous with changes in credit quality. However, this effect should be minimized because the questionnaire used to collect the information about business stage did not use any mention of credit quality to define the various business stages.

Table 1. Loan Relationships Sampled by Size and Risk Class

	Total Outstanding Relationship Balance			
Risk Class	Small <$100k	Medium $100-$400k	Large >$400k	Total
Low	95	98	96	289
Medium	79	80	67	226
Loss	41	24	9	74
Total	215	202	172	589

Table 2. Description of the Standardized 5-Tiered Risk Rating System.[a]

Level	Description
1	• 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	• 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	• 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	• 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	• 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 principal are in excess of 90 days past due or classified as non-accrual. • Repayment likely depends upon collateral.

[a] The descriptions of the regulatory classifications (4 and 5), draw heavily on the descriptions provided in "Rating Credit Risk" of the Comptroller's Handbook (pages 16-18). The descriptions of tiers 1, 2, and 3 were developed directly from information provided by the participating financial institutions.

Table 3. Financial Conditions Faced by New York State Farms, 1998-2001.

Financial Condition	1998	1999	2000	2001
Net Cash Income per Farm[a]	$ 20,484	$ 24,675	$ 26,439	$ 27,428
Debt to Asset Ratio[b]	18%	18%	18%	18%
Total Rate of Return on Assets[b]	1.93%	1.88%	3.02%	6.53%
Farm Debt Coverage[b]	1.88	2.20	2.26	2.34

[a] Economic Research Service, USDA, U.S. and State Farm Income Database.
[b] Economic Research Service, USDA, Farm Balance Sheet Database.

Table 4. One-Period Risk Migration Matrices.[a]

		2001 Risk Rating					
		1	2	3	4	5	Total
		-----------------------------		% of Borrowers		-----------------------------	
2000 Risk Rating	1	93.8	5.6	0.0	0.6	0.1	32.5
	2	1.3	91.4	3.0	3.9	0.3	40.3
	3	2.1	2.1	88.9	4.1	2.8	12.4
	4	0.0	0.0	1.2	90.0	8.9	7.8
	5	3.8	0.0	0.0	1.5	94.7	7.1
	Total	31.5	39.0	12.3	9.4	7.9	
		2000 Risk Rating					
		1	2	3	4	5	Total
		-----------------------------		% of Borrowers		-----------------------------	
1999 Risk Rating	1	97.4	2.6	0.0	0.0	0.0	32.0
	2	1.3	94.4	2.1	1.9	0.3	41.7
	3	0.0	3.1	89.9	2.6	4.3	12.2
	4	0.0	0.0	7.6	84.1	8.3	7.5
	5	0.0	0.0	0.6	8.0	91.4	6.7
	Total	31.7	40.6	12.4	7.9	7.4	
		1999 Risk Rating					
		1	2	3	4	5	Total
		-----------------------------		% of Borrowers		-----------------------------	
1998 Risk Rating	1	98.6	1.4	0.0	0.0	0.0	32.3
	2	0.0	98.0	0.9	1.0	0.2	42.0
	3	0.0	0.0	97.1	2.9	0.0	11.0
	4	0.0	4.1	4.1	90.9	0.9	7.5
	5	0.0	0.4	1.4	1.7	96.5	7.2
	Total	31.9	41.9	11.5	7.7	7.1	

[a] The sample size was 576 for the 2000-2001 matrix, 551 for the 1999-2000 matrix, and 521 for the 1998-1999 matrix.

Table 5. Two-Period Risk Migration Matrices.[a]

		2001 Risk Rating					
		1	2	3	4	5	Total
		-----------------------------% of Borrowers -----------------------------					
1999 Risk Rating	1	90.9	8.2	0.3	0.6	0.1	32.0
	2	2.7	86.2	4.7	5.6	0.9	41.7
	3	2.3	5.4	79.3	5.7	7.3	12.2
	4	0.0	0.0	8.9	76.7	14.4	7.5
	5	4.2	0.0	0.0	8.0	87.8	6.7
	Total	30.7	39.2	12.4	9.5	8.3	
		2000 Risk Rating					
		1	2	3	4	5	Total
		-----------------------------% of Borrowers -----------------------------					
1998 Risk Rating	1	95.8	4.1	0.1	0.0	0.0	32.3
	2	1.4	92.1	2.9	3.0	0.6	42.0
	3	0.0	3.7	86.8	4.1	5.4	11.0
	4	0.0	4.1	12.2	75.3	8.4	7.5
	5	0.0	0.4	2.0	9.7	87.9	7.2
	Total	31.6	40.7	11.9	8.0	7.9	

[a]The sample size was 551 for the 1999-2001 matrix and 521 for the 1998-2000 matrix.

Table 6. Credit Risk Migration Matrix for 1998 to 2001.[a]

		2001 Risk Rating					
		1	2	3	4	5	Total
		-----------------------------% of Borrowers -----------------------------					
1998 Risk Rating	1	88.9	9.9	0.3	0.8	0.0	32.3
	2	2.9	84.7	4.8	6.4	1.3	42.0
	3	2.8	3.7	78.0	5.6	9.9	11.0
	4	0.0	4.1	13.6	71.6	10.7	7.5
	5	4.2	0.0	1.4	10.1	84.3	7.2
	Total	30.6	39.5	11.8	9.7	8.5	

[a]The sample size was 521.

Table 7. Proportion of Borrowers with Changes in Credit Risk Over a 4 Year Period.

Risk Rating	Percent of Portfolio[a,b]	Percent of Sample[b]
No Change in Credit Risk	83.9%	73.3%
Experienced Change in Credit Risk	16.1%	26.7%
Upgraded	4.8%	4.4%
Upgraded more than one category	1.08%	1.2%
Downgraded	11.8%	23.0%
Downgraded more than one category	4.28%	12.3%

[a]Population estimates based upon sample of 521 borrowers.
[b]The 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 8. 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 9. Parameter Estimates for Credit Quality Downgrade Model.

Parameter	Estimate	Marginal Effect	Wald Chi-Square Statistic
Intercept	-1.0341		2.67*
ADB	1.00E-06	0.0000	6.54**
ADB^2	-9.00E-14	0.0000	2.50
Lender 1	-0.0844	-0.0153	0.05
Lender 2	0.8734	0.1585	5.23**
Lender 3	-0.7859	-0.1427	3.27*
Wald Chi-Square Statistic for LRT of Lender Group: 18.27**			
Tier 2 Risk	0.6918	0.1256	4.28**
Tier 3 Risk	1.4202	0.2578	11.27**
Tier 4 Risk	-0.4546	-0.0825	1.16
Wald Chi-Square Statistic for LRT of Risk Group: 22.28**			
Beginning Farmer	-0.1482	-0.0269	0.02
Growth Business	-0.3214	-0.0583	0.84
Declining Business	1.5791	0.2867	22.10**
Wald Chi-Square Statistic for LRT of Business Stage Group: 25.65**			
Single Borrower	0.4725	0.0858	1.14
Silver Year Borrower	-0.6605	-0.1199	4.19**
Retirement	-1.8974	-0.3444	6.17**
Wald Chi-Square Statistic for LRT of Personal Stage Group: 11.10**			
Dairy	-0.9375	-0.1702	3.20*
Annual Crops	-0.6296	-0.1143	1.34
Other Livestock	-1.4595	-0.2649	4.14**
Perm. Plantings	-0.5582	-0.1013	0.73
Green Industry	-1.791	-0.3251	4.73**
Wald Chi-Square Statistic for LRT of Industry Group: 7.46			
Likelihood Ratio Test Statistic for Model Significance: 88.97**			
Chi-Square statistic for Hosmer and Lemeshow Goodness of Fit Test: 9.90			
N= 411			

*indicates significance at the 0.10 level
**indicates significance at the 0.05 level

Table 10. Actual and Predicted Credit Quality Downgrades.[a]

		Actual		
		No Change	Downgrade	Total
Predicted	No Change	268	80	348
	Downgrade	26	37	63
	Total	294	117	

[a]With 0.50 as the probability cut-off value.

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