Farm-Level and Macroeconomic Determinants of

Farm Credit Migration Rates

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Abstract

This study utilizes probit regression techniques for panel data under a random-effects framework to identify factors that significantly influence the probability of farm credit migration rates. The results indicate that most farm-specific factors do not have adequate explanatory influence on the probability of credit risk transition. Transition probabilities are instead more significantly affected by changes in macroeconomic conditions. Economic growth signals, deduced from increasing stock price indexes and farm real estate values, and higher money supply levels relaxing the credit constraint are associated with the likelihood of class upgrades. Interest rates, normally used as a credit rationing and risk management device by lenders, negatively affect such probabilities.

Key words: credit risk migration, credit scoring, financial performance ratios, macroeconomic factors, random effects model, solvency, transition probabilities

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Migration analysis, a probability-based measurement concept, has been long employed as a routine approach by such companies as Moody's and Standard and Poor's in evaluating changes in the risk rating of bonds and other publicly traded securities. The concept has been more recently used as an analytical framework for developing probability estimates of financial stress and/or default rates for commercial, agricultural and other types of loans (Saunders; Caoutte, Altman, and Narayanan; Barry, Escalante, and Ellinger).

The migration approach entails tracking an individual borrower's historic rates of movement among the lender's credit risk rating classes within a specified time period. These migration rates are then extrapolated to formulate projections of the credit quality of the lender's entire portfolio according to overall trends in class upgrades versus downgrades and derived estimates of probability of loan default or stress rates.

Such migration-based measures of credit risk could be used as important inputs in the determination of the regulatory requirements for economic capital held by lenders under the proposed New Basel Accord (Barry). Compared to the traditional measurement of historic loan default rates, the credit risk estimates obtained through the migration approach provide richer, much broader information on the risk stability and quality of a lender's loan portfolio, especially when based on more extensive historical data.

In the area of agricultural lending, a number of lenders, especially Farm Credit System institutions, have already ventured into using the credit migration concept to analyze their loan portfolios, although their data histories tend to be shorter at less than five years in length and updating of the borrower’s financial data can be sporadic. In the agricultural finance literature, Barry, Escalante and Ellinger have utilized longitudinal farm-level data to produce estimates of transition probability rates, overall credit portfolio upgrades and downgrades, and financial stress rates of grain farms in Illinois over a fourteen-year period. Their study demonstrates the practical relevance of the migration framework in the assessment of credit portfolio qualities and its potential appeal to farm lenders still developing their own credit risk measurement frameworks.

This study pursues the application of migration analysis to agricultural loans through a more in-depth analysis of possible factors that may influence the volatility of migration rates among farm borrowers. The analysis focuses on three sets of factors related to farm structure, financial performance, and macroeconomic conditions that are expected to influence changes in credit risk class ratings over time. The first two variable groups are associated with the farm business and most represent a choice set of business decision variables that are within the farm manager's control. The third set of factors represents macroeconomic cycles that are exogenous conditions that cannot be controlled by individual farms. Possibly the credit migration tendencies of certain farms could be more vulnerable to these cycles compared to other farm businesses (Estrella). This is corroborated by studies investigating on corporate bond defaults which have established strong linkages between deteriorating economic conditions and greater transition to default of high-yield corporate bonds (Helwege and Kleiman; McDonald and Van de Gucht; Nickell, Perraudin and Varotto).

Consistent with the recommendations of the Basel Accord, this study also applies the migration and econometric frameworks to an expanded credit rating system involving ten credit classes. Important implications are derived from a comparison of the results of this analysis to those obtained under the conventional five-class rating model.

The following sections explain the mechanics of the migration framework, discuss the development of the empirical framework, and present the results of the descriptive and econometric analyses.

Measuring Rates of Migration

There are two important considerations in the application of credit migration analysis: the choice of classification variable and the type of migration measurement approaches. Several options for the classification variable include measures of profitability (return on equity), repayment capacity and the credit score, which is a composite index of credit risk that usually includes the latter measures and other financial factors.

In this study, a farm's credit score is used to assign farmers into different credit risk classes. This will be determined through a uniform credit-scoring model for term loans reported by Splett et al. that is based on financial ratios recommended by the Farm Financial Standards Council representing a farm's solvency, repayment capacity, profitability, liquidity and financial efficiency. This study will follow the measurement procedures, the pre-determined weights assigned to each component of the credit-scoring model and classification intervals used by Splett, et al. which are reported in Table 1.

Table 1 also presents the expanded 10-class rating model, which has been recommended under the Basel Accord to more accurately capture differences in credit classifications of prospective bank borrowers. The class boundaries are actually based on the original five-class rating model where, for example, class 1 in the latter model has been broken down into classes 1 and 2 of the ten-class rating model. The same trend applies to the subsequent classes in the rating models.

Outlier values for the current ratio and the repayment capacity measures will be replaced by maximum values used by Barry, Escalante and Ellinger, i.e. current ratios exceeding the value of 7 were assigned the maximum value of 7 while the equivalent bounds (-1.25 to 0.93) for the repayment capacity measure suggested by Novak and LaDue were used in this study.

The classification criterion, a farm's credit score, will be evaluated using various measurement approaches, involving different sample sizes and time sequences of data employed in the measurement process. This study will use the following measurement approaches in determining migration rates:

i) Year-to-Year Transition (1 x 1), which measures movements in credit risk ratings given in a particular year (n) to those assigned to the borrower in the succeeding year (n + 1); and

ii) Three-Year Average to Fourth Year (3 x 1), which measures the transition from a credit score rating based on the average of the first three years to the risk rating given to the borrower on the fourth year.

Results under the annual and 3x1 migration approaches will be compared to discern changes in migration trends and their determinants under more immediate versus gradual (three-year) transition in farm financial performance. The 3x1 approach is informally acknowledged as a popular approach used by farm lenders.

Proxy Lender and Macroeconomic Data Sources

In lieu of actual lender data which are difficult, if not impossible, to obtain, this study utilizes information from farm financial records as proxy for actual performance of borrowing farms. This approach places greater emphasis on quantitative measures of credit risk and isolates the influence of the lenders' subjective appraisal of potential credit risk and disregards the relevance of possible risk mitigation strategies employed by some lenders through certain pricing and non-pricing components of the loan covenants. Moreover, this study recognizes the fact that the use of farm record data could include both classes of borrowers with low credit risk (among non-borrowing farms) and high credit risk (accommodated under special financing programs from the government.

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

The inclusion of a risk variable calculated as a three-year moving average and the determination of year-to-year migration rates resulted in 8 observations for each farm under the annual migration approach. The other two migration approaches (3 x 3 and 3 x 1) required groups of 4 annual observations to calculate a migration rate, thus resulting in just 7 observations for each individual farm.

The macroeconomic measures considered in this study were obtained from databases of various institutions that publish them either in print, online, or both. Annual averages of Illinois farm real estate values and long-term agricultural lending rates were obtained from the annual agricultural finance publication of the U. S. Department of Agriculture. Annual changes in S&P

500 were obtained from the Standard and Poor's website while data on consumer price indexes and money supply levels were available online through the Federal Reserve Bank of St. Louis website.

The Transition Probability Matrices

The average one-period transition matrices for the year-to-year (1 x 1) and three-year average-to-fourth year (3 x 1) measurement approaches are reported in Table 2. These matrices were constructed by comparing the credit classifications in two subsequent periods. In the table, the credit classes in the vertical axis correspond to Period 1 classes while the horizontal axis shows credit classifications by the end of the second period. Between these two periods, the matrix measures the probability that a farm business will experience a transition from the row classes to the column classes at the end of each period. This probability is calculated as the ratio of the number of farms that migrate to a certain column class (in Period 2) to the total number of farms originally classified under a particular row class (in Period 1).

In the resulting migration matrices in Table 2, the values along the diagonals represent the retention rates, or the probabilities that farms will remain in their row classes in Period 2. The off-diagonal elements represent the percentages of upgrades and downgrades in credit classification. Specifically, a movement to the right of each diagonal indicates a downgrading of credit risk class while a movement to the left is a credit class upgrade.

The matrices presented in Table 2 are confined to a fixed, finite set of 116 farms evaluated during the period 1992-2001. This closed system does not accommodate either new entrants into the classification system or exiting farms among those that fall in the default category (i.e. Class 5). Financially distressed farms in Class 5, therefore, could either remain in the default class or experience a class upgrade during the 10-year period in the absence of a rating withdrawal class, which is a typical component of transition matrices developed for corporate bonds.

The migration rates for the five-credit classification system in Table 2 are generally close to values reported by Barry, Escalante and Ellinger, although their transition probability matrices were constructed using a longer time frame (1985-1998) and the migration rates were separately calculated using all available farm observations in each pair of subsequent time periods, without the panel data structure restriction used in this study. The year-to-year average retention rates in this study range from 28.13% to 73.31% while the 3 x1 measurement approach yielded retention rates ranging from 22.87% to 77.18%. Consistent with the results of Barry, Escalante and Ellinger, the retention rates in this study are highest for Class 1 borrowers, tend to diminish for the middle lower credit risk classes and slightly increase in Class 5.

The retention rates under the expanded 10-credit classification system (Table 3) tend to be significantly lower than those obtained when using five credit classes. As before, Class 1 farms have a greater tendency to remain in their classes compared to farms in the other credit classes. Retention rates for Class 1 farms were calculated at 65.03% and 63.64% for the 1x1 and 3x1 measurement approaches, respectively. The rest of the retention rates, however, do not exhibit a monotonically decreasing trend as the credit class rating deteriorates, similar to the trend observed in the middle lower classes under the 5-credit classification system. In Classes 2 to 10, the retention rates range from 12.73% to 32.00% in the 1x1 approach and 12% to 44% in the 3x1 approach. These results are significantly lower than those determined using the 5-class rating approach.

Interestingly, under a 7-bond rating scale (between the 5 and 10 class rating scales used here), Moody's bond rating retention rates in a one-year transition matrix ranged from 56% to

88.3% during the period 1983-1998. A similar matrix developed by S & P for the period 1981-1996 yielded retention rates ranging from 53.1% to 88.5%. In contrast, this study reports average retention rates of only 50.43% and 31.57% using under the 5 and 10 class rating systems, respectively under the 1x1 measurement approach (Table 4).

In general, studies on bond migration normally reflect a tendency toward more downgrading than upgrading of class ratings. For example, Altman and Kao, analysing first rating changes among bonds, report that of the total migration of AA bonds, 83.5% are downgrades and 16.5% are upgrades. Rating migration of A bonds, on the other hand, is broken down into 57.1% downgrades and 42.9% upgrades. In this study, this trend is only realized under the 1x1 approach, regardless of credit classification system used. Specifically, upgrades and downgrades account for 46.74% and 53.26% (23.17% and 26.40%, inclusive of class retention rates), respectively, of the total transition to other credit classes using 5 credit classes (Table 4). The corresponding figures for the 10 class approach are 46.46% and 53.54% for upgrades and downgrades, respectively.

The trend is reversed for upgrades and downgrades under the 3x1 approach. Apparently, the three-year averaging method used for determining Period 1 classes could possibly cushion the impact of volatile and even adverse financial conditions on the farm's resulting initial credit risk rating.

Econometric Framework

The empirical framework utilizes time-series cross-sectional probit regression technique performed using version 7.0 (Special Edition) of Stata software. Four versions of the estimating model are developed using the two measurement approaches (i.e. annual and 3 x 1 migrations) for each of the five- and ten-credit classification systems.

Hausman's specification test results indicate that the stochastic (random) component of the error term and the regressors are correlated, which provide justification for the application of the random-effects model. A Stata procedure designed to perform probit regression technique for panel data under the random-effects framework is therefore used for this analysis. The general conceptual form of the estimating equations is:

(1) $$Y_{it}^{*} = \alpha + V_{it}'\beta_1 + W_{it}'\beta_2 + Z_{it}'\beta_3 + \mu_i + \varepsilon_{it}$$

where Y_{it}, the event of interest, is an ordered, discrete migration variable, evaluated on every pair of subsequent periods, that takes on a value of 2 for every upgrade of credit classification, a value of 1 for remaining in the same class (retention) and a value of 0 for a downgrade in credit classification; α is the model's general intercept; the V_{it}, W_{it}, and Z_{it} vectors (with their corresponding vectors of regression coefficients β_1, β_2 and β_3, respectively) are associated with three groups of independent variables representing structural/demographic, financial and macroeconomic factors that could influence the probability of class migrations; and μ_i and ε_{it} are the model's error terms, with the latter representing the stochastic unit-specific error components. Under the random-effects framework, the error terms are assumed to demonstrate the following properties (Greene):

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

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

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

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

Probit regression is a log-linear approach to handling categorical dependent variables using the cumulative normal distribution. Thus, in this analysis, the cumulative normal probability that, for instance, a credit upgrade ($Y_{it} = 2$) occurred is specified as a nonlinear (probit) function of farm/farmer's demographic and structural attributes(V_{it}), financial characteristics of the farm business (W_{it}) and prevailing macroeconomic conditions (Z_{it}). Moreover, while the dependent variable Y_{it} in equation (1) is a latent, unobserved random variable, the observed migration rate denoted by Y_{it}* is determined as:

$$Y_{it}^* = 0 \text{ if } Y_{it} \leq 0$$

(2) $$Y_{it}^* = 1 \text{ if } 0 \leq Y_{it} \leq \eta_1$$

$$Y_{it}^* = 2 \text{ if } \eta_1 \leq Y_{it} \leq \eta_2.$$

where η_1 and η_2 are unknown parameters that collectively define the range of values into which the latent variable may fall (Greene). The η's are to be estimated, along with the unknown β's, coefficients of the explanatory variables.

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

$$Prob\ (Y_{it}^* = 0) = \phi(-B'X)$$

(3) $$Prob\ (Y_{it}^* = 1) = \phi(\eta_1 - B'X) - \phi(-B'X)$$

$$Prob\ (Y_{it}^* = 2) = \phi(\eta_2 - B'X) - \phi(\eta_1 - B'X)$$

where the function $\phi(.)$ indicates a standard normal distribution, X is a vector containing the three groups of regressors V_{it}, W_{it} and Z_{it}, and the vector B contains their corresponding coefficients β_1, β_2, and β_3.

The specific components of the three groups of regressors and their hypothesized effects on the dependent variable are discussed in detail in the following sub-sections.

Structural and Demographic Factors

This analysis considers the significance of certain structural factors related to farm size, farmland control arrangements, enterprise diversification strategies and productivity of existing farm asset complement in influencing the economic and financial resiliency of the farm business. Farm size (SIZE), which is measured in gross revenues, could potentially influence the probability of upward migration since larger farms usually possess the greater capability to achieve improved production efficiencies under economies of scale. These benefits, however, could be tempered by leverage decisions that are non-optimal, create greater financial stress for the farm business and decrease the probability of an upgrading of the farm's credit risk rating.

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

Substantial reductions in risk realized through enterprise diversification could also determine the probability of upward credit migration. In this study, an enterprise diversification index (DIVER) is constructed for each farm using the Herfindahl measure of concentration, calculated as

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

The index is based on the breakdown of gross farm revenues among receipts realized from the sale of crops, livestock and auxiliary farm services/products. Under this approach, a fully specialized farm takes on an index value of 1 while smaller index values indicate more diversified business portfolios. The overall influence of the diversification strategy on this model's dependent variable will depend on tradeoffs between risk reduction (resulting from the diversification strategy) and high revenue potentials (through comparative trade advantages enjoyed by specialized grain farming operations in North Central Illinois (Barry, Escalante and Bard).

The influence of the farm's asset acquisition decisions can be discerned through an asset productivity measure, the asset turnover ratio (ATO), calculated by dividing gross farm revenues by total farm assets. Farms that continue to hold idle assets and obsolete equipment incur additional maintenance costs and forego the liquidity benefit that can be enjoyed from the liquidation of these assets as well as the productivity (and profitability) gain from the replacement of such assets with more efficient, newer assets.

In addition to these structural factors, three demographic variables pertaining to the farm operator's age, the farm's geographical location and the soil's productivity rating are also included in the models. The effect of AGE on the dependent variable is deduced from previous empirical studies that contend that older farmers tend to be more risk averse (Patrick, Whitaker and Blake; Lins, Gabriel and Sonka). These farmers are expected to implement more cautious business plans that do not always realize the full growth potential of their farm businesses.

Opportunities for improvements in credit risk could possibly be greater among farms located near or within large urban areas given their proximity to more established marketing channels and providers of production, technical and financial support. In this study, the location factor is represented by URBINF, an urban influence dummy variable based on a USDA index that classifies counties into 9 mutually exclusive groups based on the adjacency to metro areas, which are categorized according to size or population. This analysis simplifies the index into a binary dummy variable that takes a value of 1 for counties within or adjacent to large metropolitan areas with about 1 million residents (USDA's codes 1-4) and a value of 0 for non-metropolitan counties that are either adjacent to a smaller metropolitan areas or are considered totally rural and isolated communities (USDA's codes 5-9).

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

Farm Financial Indicators

The original intention was to include in the estimating models all five financial variables that collectively determine the farm's credit score. These measures are based on financial ratios recommended by the FFSC and represent a farm's liquidity, solvency, repayment capacity, profitability and financial efficiency. Preliminary diagnostic tests yielded very high condition index numbers (over 100) and variance inflation factors (over 30) due to the interdependence of some of these measures, such as the equity-asset ratio (solvency), return on equity (profitability) and net farm income ratio (financial efficiency). The results suggest serious multicollinearity problems for the models.

In order to resolve the problem, the profitability measure was dropped from all estimating models, while retaining measures of solvency (SOLV), financial efficiency (INCRAT) and liquidity (current ratio, CURAT). In the annual migration models, the repayment capacity variable (capital-debt repayment margin ratio, REPMT) is also added due to its minimized correlation with the other variables. Improvements in any of these financial measures included in the models are expected to increase the probability of credit class upgrades.

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

Macroeconomic Variables

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

Among alternative proxy measures for economic growth activity, the annual average level or growth rate of farm real estate values (FLAND and FLGRWTH, respectively) provide a more comprehensive indication of growth both within the farm industry and the economy in general. In certain versions of the model, a farmland growth rate variable performs better as a regressor than the absolute measure. Variation in the growth of farm real estate prices does not only depend on farm-related conditions such as changing government farm policies, production risks and farm credit conditions, but also on non-farm investment opportunities dictated by the economy's demands for commercial, residential and recreational facilities, among others.

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

The credit cost factor is represented in this study by average interest rates for agricultural mortgage (long-term) loans (AGRATES). Interest rate adjustment is normally among the policy options used by the Federal Reserve Board (FRB) to achieve certain economic goals. For instance, the FRB's aggressive rate-cutting campaign in recent years was designed to keep a sluggish economy out of recession by stimulating greater economic activity from the business, consumer and market sectors of the economy. Compared to short-term interest rates that are easily affected by changes in the federal funds rate, longer-term borrowing rates follow a more complicated adjustment process that involves other indicators, such as speculative and precautionary factors. Moreover, interest rates could serve as a credit risk management tool for commercial lenders that charge differential loan pricing rates according to the perceived credit risk profile of their individual borrowers.

Finally, credit risk migration could also be affected by the general economic outlook of the investment community as reflected in both the prices being paid for holding financial assets, such as stocks, and the risk premium that investors are willing to pay for keeping riskier vis-à-vis less risky financial assets (Altman). The Standard and Poor (S&P) 500 index of stock prices is used as proxy for the overall stock market performance. In this study, annual changes in the stock price index (SPCHG) are calculated to reflect changes in the investors' demand for holding stocks as financial investments.

Econometric Results

Except for the income risk variable, the dependent variable is regressed against the two-year and four-year averages of the annual values of the explanatory variables under the annual and 3 x1 migration frameworks, respectively. Moreover, diagnostic test results indicate the need for a modified version of the estimating equation for the annual migration approach vis-à-vis the version for the 3 x 1 migration approach in order to avoid the effects of multicollinearity, heteroscedasticity and serial autocorrelation in each of the datasets. The resulting versions of the time-series cross-sectional probit estimating equations are:

1) Annual Migration Approach:

Y_{it} = f(SIZE, TENURE, DIVER, ATO, AGE, URBINF, SOIL, SOLV, INCRAT, CURAT, REPMT, INCRISK, FLAND, MONEY, AGRATES, SPCHG)

2) 3 x 1 Migration Approach:

Y_{it} = f(SIZE, TENURE, DIVER, ATO, AGE, URBINF, SOIL, SOLV, INCRAT, CURAT, INCRISK, FLGRWTH, MNYGRWTH, AGRATES, SPCHG)

Since the dependent variable in each model is defined as an ordered three-level variable (for upgrades, retentions and downgrades), the directional effects of each independent variable for all three categories of the dependent variable could not be deduced from the sign and magnitude of its coefficient estimates. The models' coefficients could only provide unambiguous indications of changes in the probability of moving from the highest to lowest categories, and vice versa, in addition to important information on the models' explanatory power and the relative statistical significance of each individual independent variable. The regressors' directional effects can be discerned, however, from estimates of their marginal effects. The following sections separately discuss the significance of certain variables and their specific directional effects in each category of the dependent variable.

Significant Determinants

Table 5 reports the coefficient estimates and the resulting Z-statistics for the significance tests for the four versions of the model.[1] A positive (negative) coefficient for a regressor suggests that a similar magnitude of increase (decrease) in the probability of a credit class upgrade and a decrease (increase) in the probability of a class downgrade is associated with every unit increase in the value of the independent variable.

Notably, among the three groups of regressors, none of the 7 demographic and structural variables had a significant influence on the probability of credit migration in 3 of the 4 models. This result could be reflective of the distributional characteristics of the dataset with possibly homogenous demographic and structural attributes producing variability that is not enough to significantly affect credit migration probabilities. Moreover, it is suspected that certain variables could have an interaction effect where two attributes (eg. farm size and solvency) have dual, offsetting effects on the dependent variable. For example, larger farms that have larger built-in production capacity could more likely experience credit upgrades, but they could be highly leveraged and exposed to greater business and financial risks that, in turn, increases the chance of a credit risk downgrade.

Two variables in this category are, however, significant in the fourth model, the 3x1 measurement approach using 10 credit classes. These are the diversification (DIVER) and soil productivity (SOIL) variables which had negatively signed coefficients. DIVER's negative coefficient suggests that increasing specialization of farm enterprises could lead to greater probability of class downgrades. This result is reinforced by SOIL's negative coefficient, which indicates that lower soil ratings tend to enhance the probability of class downgrades. These results aptly describe the regional distribution of farm operations in Illinois where the relatively less productive soil profiles of the Southern counties create a greater necessity to diversify farm enterprises by engaging in a mix of crop and livestock production. In contrast, the highly productive soils in the North and Central regions normally allow their farms to benefit from comparative advantages realized from specializing in corn, soybean and wheat production. However, this study's sample period captures episodes of steadily declining grain prices as a result of supply overstock in the mid-1990s while federal programs wavered from providing risk-reducing countercyclical to fixed, decoupled payments. Hence, the more diversified crop-livestock farms in less productive regions have been relatively more resilient and have been more likely to realize upward mobility in credit risk ratings.

Nonetheless, the overall weak, insignificant impact of the farm's structural and demographic profile could imply that the importance of such attributes could be more emphasized only at the credit screening and rationing stage when these parameters are used as bases for making loan decisions and defining the provisions of the loan covenant. Once the loan is granted and serviced, these factors become less relevant in determining periodic transitions in credit quality, which instead depend on other sets of factors, which are not necessarily farm-specific.

The significant variables that are within the farm manager's control are two measures of financial performance. These are financial efficiency (INCRAT) and liquidity (CURAT), which are positively related to the dependent variable.[2] INCRAT, which is significant in all 4 models, captures the relative importance of revenue enhancement, profitability and cost efficiency in improving business performance. These conditions, combined with the liquidity effect from the CURAT variable, ensure that a farm that is able to adequately cover its operating and debt servicing fund requirements would more likely be able to experience improvements in its credit risk classification.

Interestingly, the probability of credit quality improvements is not significantly affected by the farm's solvency[3] and income risk conditions in this analysis. The time frame used in this study is characterized by a generally healthy farm credit environment due to stricter credit rationing policies by lenders and more prudent borrowing decisions made by farmers. These produced relatively lower loan delinquency rates while the farm sector maintained stable overall leverage ratios during the 1990s. During the same period, the steady plunge of commodity prices and the wavering stance of federal policy toward countercyclical farm subsidies only potentially or temporarily increased income risk conditions in the farm sector. Eventually, large adhoc government appropriations for the farm sector responding to the looming farm financial crises stabilized farm incomes and reduced their variability over the years.

The overwhelming result in this study is the strong influence of macroeconomic variables on the dependent variable. Long-term agricultural interest rates (AGRATES) and annual changes in the value of the S&P index (SPCHG) are the consistent significant performers among the macroeconomic variables. AGRATE's negative coefficient indicates that increases in borrowing rates as a result of stricter credit rationing and protective risk management policies under a riskier credit environment would be associated with higher probability of credit class downgrades. On the other hand, SPCHG's positive coefficient is consistent with the expectation that a growing stock market index, associated with a booming economy with more aggressive investors preferring riskier stock investments over fixed income instruments, could influence the probability of realizing upgrades in credit risk ratings.

Money supply (MONEY) and changes in farm land values (FLGRWTH) alternate in significance in the 1x1 and 3x1 models, respectively. Higher MONEY values relax the credit availability constraint and, thus, allow farms to undertake freely operating and capital strategies designed to achieve growth and increase the likelihood of realizing improvements in credit risk. FLGRWTH has a similar positive effect on the dependent variable. Increases in farm real estate values do not only (and necessarily) point to a flourishing farm economy but also signal a growing economy with expanding construction demand in commercial, residential and recreational areas. Under this condition, the probability of realizing upgrades in credit quality also increases.

Directional Effects

The directional effects are more explicitly given by estimates of the marginal effects of the significant explanatory variables in Table 6. Marginal effects reported in the table were computed by adopting techniques from the ordinal probit regression routine in Stata. The marginal effects for each category of the dependent variable are calculated as follows using the probabilities defined in the series of equations in (3):

$$
(4) \qquad
\begin{aligned}
\frac{\partial \Pr ob(Y_{it}^{*}=0)}{\partial X} &= -\phi(\beta' X)\beta, \\
\frac{\partial \Pr ob(Y_{it}^{*}=1)}{\partial X} &= (\phi(-\beta' X) - \phi(\eta - \beta' X))\beta, \\
\frac{\partial \Pr ob(Y_{it}^{*}=3)}{\partial X} &= \phi(\eta - \beta' X)\beta,
\end{aligned}
$$

Based on the calculated estimates of marginal effects in Table 6, among the financial measures under the farm manager's control, the probability of experiencing a downgrade is more sensitive to unit changes in financial efficiency (INCRAT) than to similar increments in the liquidity variable (CURAT). Specifically, the likelihood of a downgrade decreases by a range of 8.7% to 19.7% due to a unit increase in INCRAT while the equivalent change for CURAT is within a range of 0.3% to 0.8% only. The probability of retentions and upgrades would increase for every unit change in each of these two financial variables, with INCRAT eliciting a greater influence on the retention and upward migration probabilities than CURAT.

The positively signed macroeconomic variables (SPCHG, MONEY and FLGRWTH) in Table 5 consistently have a negative and a positive effect on the probability of a class downgrade and upgrade, respectively, in Table 6. Their directional effects on the retention probability, however, are not homogenous. Unit changes in SPCHG and FLGRWTH lead to decreases in retention probability of about 2.8% to 3.6% and 42.6 to 66.3%, respectively, in the 3 x 1 models. In contrast, a unit increase in SPCHG causes the retention probability to increase by about 5.3% to 6.1% in the 1x 1 models. The same effect applies to the MONEY variable which causes the retention probability to increase from 0.02% to 0.03% in the same models.

AGRATES, a negatively signed regressor in Table 6, yielded the strongest results among all variables. This variable consistently influences changes in downgrade probabilities within a range of 43.3x to 56.3x. The results are mixed for retention probabilities, with the variable negatively affecting the probability in the 1 x 1 models while having a positive effect in the 3 x 1 models. The variable's effect, however, is consistently negative for the probability of a class upgrade.

Summary and Conclusions

This study introduces two new perspectives in understanding the application of the migration model to farm credit risk analysis, i.e. a modified credit classification system and possible determinants of credit migration probabilities. Consistent with the recommendation of the Basel Accord, an expanded 10-class version of the five-class credit rating system is introduced and its consequent impact on transition probabilities of farms is presented. An econometric framework was also developed to identify determinants of the probability of credit risk migration among factors that are both within and beyond the farm manager's control.

The migration matrices obtained in this study reflect the expected trend of lower class retention rates and highly volatile transition probabilities compared to results obtained for bonds and other publicly traded securities (Barry, Escalante, and Ellinger; Altman and Kao). This result is consistent with the riskier nature of farming operations that are easily more susceptible to seasonal fluctuations in weather and market conditions than firms belonging to other industries. Notably, the shift from the conventional 5 credit classification system to an expanded 10-class approach produced greater incidence of class migrations with higher overall rates of upgrades and downgrades than retention rates, which are significantly lower than the rates obtained under the former classification scheme.

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

Solvency is neither a significant determinant of migration probabilities, although it remains to be an important variable in determining the initial risk classes given its relatively large weight in the scoring model. The relatively less turbulent credit atmosphere in the 1990s which elicited more cautious borrowing behavior and more effective credit rationing practices by lenders stabilized the farm industry's leverage conditions. Moreover, income risk, due to the smoothening effect in farm incomes of substantial federal subsidies to the farm sector, did not significantly affect the likelihood of credit migration. Business strategies designed to maximize the farms' liquidity and profitability potential are the only farm-specific factors that effectively influence credit migration probabilities.

The more overwhelming result is the dominance of the effects of macroeconomic factors on the probability of credit migration. Increases in stock price indexes and farm real estate values that both signal a growing economy through aggressive investment activities and expansive project developments are associated with the likelihood of class upgrades. The relaxation of the credit constraint through higher levels of money supply also has a similar effect on credit migration probabilities while interest rates, often used as a credit rationing and risk management device by lenders, negatively affect such probabilities.

Notes

1. Regression runs were also made on “disaggregated” versions of the model where the original estimating equations were decomposed into two groups: a first regression run involving only the structural and macroeconomic variables, and a second run focusing only on the set of financial variables used to determine the credit score. Whether or not financial variables are isolated from the estimating equations, the trend towards the dominant explanatory power of macroeconomic variables remains clear as will be discussed in the subsequent sections.
2. The average relative variability (coefficients of variation) values for these two variables over the time period are higher, especially compared to the results for the solvency variable that had the least variability.
3. The econometric framework was also applied to subsets of the entire dataset, which was partitioned into three groups according to the farms’ historical average solvency (equity-asset) ratios. Interestingly, solvency, among other factors, was a significant determinant of credit migration probabilities for the top one-third group comprised of financially distressed farms.

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Table 1. Credit Scoring, Profitability and Repayment Classification Intervals (Source: Splett, et al.)

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

CREDIT SCORE CLASSES

FIVE CREDIT CLASSES

Class 1	1.00-1.80
Class 2	1.81-2.70
Class 3	2.71-3.60
Class 4	3.61-4.50
Class 5	4.51-5.00

TEN CREDIT CLASSES[**]	
Class 1	1.00-1.40
Class 2	1.41-1.80
Class 3	1.81-2.25
Class 4	2.26-2.70
Class 5	2.71-3.15
Class 6	3.16-3.60
Class 7	3.61-4.05
Class 8	4.06-4.50
Class 9	4.51-4.75
Class 10	4.76-5.00

Note: [*] New interval ranges for the repayment capacity measure were used in this study since the intervals proposed by Splett, *et al.* resulted in the heavy concentration of observations in the first class.

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

Table 2. Average One Period Transition Matrices for Credit Scores, Five Credit Classes, 1992-2001, In Percent

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

Table 3. Average One Period Transition Matrices for Credit Scores, Ten Credit Classes, 1992-2001, In Percent

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

Table 4. Summary Transition Rates for Illinois Farms, 1992-2001, In Percent

Time Sequence	Five Credit Classes	Ten Credit Classes
Retention		
Year-to-Year Transition	50.43	31.57
Three Year Average to 4^{th} Year Transition	48.65	29.31
Upgrades		
Year-to-Year Transition	23.17	31.79
Three Year Average to 4^{th} Year Transition	26.23	36.82
Downgrades		
Year-to-Year Transition	26.40	36.64
Three Year Average to 4^{th} Year Transition	25.12	33.87

Table 5. Results of Random-effects Probit Regression, Annual and 3 x 1 Transition Models, Five and Ten Credit Classes, Multinomial Dependent Variable (Upgrades=2, Retention=1, Downgrades=0)

Variables	Year-toYear Transition				Three-Year Average to 4th Year Transition			
	5 Credit Classes		10 Credit Classes		5 Credit Classes		10 Credit Classes	
	Coefficient	Z-stat	Coefficient	Z-stat	Coefficient	Z-stat	Coefficient	Z-stat
Intercept	-0.00813	-0.10	-3.93835	-1.26	11.81114	2.62^{a}	10.79616	2.57^{a}
A. Demographic and Structural Variables								
Farm Size ($)	-4.42e-07	-1.23	-2.82e-07	-0.82	-3.81e-07	-0.96	-3.96e-07	-1.03
Tenure Ratio (Acres)	0.34674	1.33	0.20348	0.84	0.40013	1.38	0.12832	0.47
Diversification Index ($)	-0.04576	-0.17	0.11707	0.46	-0.18880	-0.61	-0.65389	-2.23^{b}
Asset Turnover ($)	0.48358	1.48	0.51030	1.68	0.10346	0.30	0.34535	1.02
Operator's Age (Years)	0.00776	1.40	0.00544	1.06	0.00457	0.77	0.00578	1.03
Urban Influence Dummy	-0.01139	-0.10	-0.10999	-1.06	0.06277	0.52	0.09873	0.97
Soil Rating	0.00117	0.23	-0.00205	-0.43	0.00290	0.51	-0.00945	-1.74^{c}
B. Financial Performance Variables								
Solvency Ratio ($)	-0.58673	-1.44	-0.00776	-0.02	-0.35576	-0.77	0.04787	0.11
Financial Efficiency Ratio ($)	1.60060	3.50^{a}	1.25165	2.92^{a}	1.43565	3.27^{a}	0.82972	2.00^{b}
Current Ratio ($)	0.12038	3.43^{a}	0.05557	1.78^{c}	0.08353	2.14^{b}	0.04518	1.26
Repayment Margin Ratio ($)	0.06109	0.49	-0.07283	-0.62				
Income Risk ($)	0.00597	0.95	0.00740	1.04	0.00350	0.64	0.00557	0.86
C. Macroeconomic Variables								
Land Value ($/acre)	0.00035	1.56	0.00031	1.49				
Land Value Growth (%)					50.23963	4.44^{a}	56.86747	5.42^{a}
Money Supply ($)	0.00927	2.75^{a}	0.01437	4.52^{a}				
Money Supply Growth (%)					-0.15675	-0.05	2.31420	0.82
S&P 500 Change (%)	2.34471	3.71^{a}	2.97698	5.04^{a}	2.18273	1.78^{c}	3.24503	2.83^{a}
Ag LT Interest Rates (%)	-131.75210	-3.59^{a}	-158.13270	-4.63^{a}	-178.75030	-3.51^{a}	-163.1224	-3.43^{a}
Log likelihood	-499.45447		-580.7530		-424.16956		-485.21572	
Wald Chi^{2}	66.38^{a}		55.97^{a}		59.60^{a}		64.68^{a}	

Note. : The superscripts a, b and c denote significance at 99%, 95% and 90% levels, respectively

Table 6. Marginal Effects of Significant Explanatory Variables, Annual and 3 x 1 Transition Models, Five and Ten Credit Classes

Significant Variables	Five Credit Classes			Ten Credit Classes		
	Downgrades	Retention	Upgrades	Downgrades	Retention	Upgrades
I. Year-to-Year (Annual) Transition						
Financial Efficiency Ratio ($)	-0.19660	0.01405	0.18255	-0.18796	0.01059	0.17736
Current Ratio ($)	-0.00342	0.00024	0.00318	-0.00813	-0.00046	0.00767
Money Supply ($)	-0.00325	0.00023	0.00301	-0.00512	0.00029	0.00483
Ag LT Interest Rates (%)	43.63109	-3.11760	-40.51349	56.32796	-3.17441	-53.15354
S&P 500 Change (%)	-0.74328	0.05311	0.69017	-1.08118	0.06093	1.02024
II. Three Year Average to 4th Year (3 x 1) Transition						
Diversification Index ($)				0.26516	0.00948	-0.27464
Soil Rating				0.00377	0.00013	-0.00390
Financial Efficiency Ratio ($)	-0.11466	0.00357	0.11823	-0.08760	0.00313	0.09073
Current Ratio ($)	-0.00487	-0.00015	0.00502			
Land Value Growth (%)	-13.67208	-0.42612	14.09820	-18.55092	-0.66297	19.21389
Ag LT Interest Rates (%)	49.21367	1.53385	-50.74752	43.31405	1.54796	-44.86201
S&P 500 Change (%)	-0.88856	-0.02769	0.91625	-1.00321	-0.03585	1.03906