Credit Risk Migration Patterns of Agricultural Loans[35]

by
Andrew Behrens and Glenn Pederson

Abstract

This study utilizes comparisons and Probit regression analysis to determine the influence of previous migrations and other variables on the likelihood of future migrations of agricultural loan credit risk. The Farm Credit System association data set contains a large number of lender risk-rated agricultural loans. The lender risk ratings used are less likely to migrate than ratings based on credit score proxies. The results indicate that the direction of previous migrations significantly influences future migrations in a trend-reversal pattern. Forecasting future migrations remains difficult even though the marginal effect of a previous migration on the likelihood of a future migration is quite large.

Keywords: credit risk migration, transition probabilities, credit scoring, credit risk, agricultural lending, credit quality

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Introduction

Several papers have recently applied credit risk migration analysis to agriculture (Philips and Katchova; Barry, Escalante, and Ellinger; Escalante et al.; Gloy et al.). However, the lack of actual loan data sets of sufficient size appears to have been a limiting factor in these agricultural studies. It is frequently the case that loan data bases are small in terms of the number of loans and the number of years that are covered. In the absence of sufficient loan data, researchers have relied on credit scores computed from year-end farm financial statements, as a proxy for credit risk ratings. These credit scores are based solely on financial data, while credit risk ratings would also include additional subjective information about the borrower and the borrower-lender relationship. Thus, it is unclear whether credit scores migrate in the same way that credit risk ratings do. The objective of this paper is to evaluate the migration behavior of agricultural loans by using a large set of actual loan-level credit risk ratings. We apply a Probit model to identify the determinants of risk migration, and we measure the marginal probabilities of migration within the data set.

It is generally accepted that there are three types of factors that induce credit risk migration. The first is the autoregressive influence of previous migrations (Phillips and Katchova; Lando and Skodeberg; Altman and Kao; Jafry and Schuermann; Bangia et al.; Christensen et al.; Wendin and McNeil). While it is generally accepted that there is a downgrade momentum among bond rating migrations, the influence of previous migrations in agricultural loan portfolios is not confirmed. Lenders as well as regulators can use knowledge of migration trends as early warning signals for changes in portfolio credit risk.

A second factor is the role of borrower-specific data (Nickell et al.; Wendin and McNeil; Escalante; Gloy et al.). This includes covariates for industry/farm type, experience, loan purpose, financial measures, loan term, and more. Many of these variables are factors considered in the loan origination process, and they are expected to influence credit risk migration. Industry/farm type is important to a lender that is investing or disinvesting in a block of similar loans. If farm type influences migration rates the resulting portfolio will migrate differently due to the new weighting.

Macroeconomic variables are a third factor that underlies migration (Phillips and Katchova; Nickell et al.; Altman and Kao; Jafry and Schuermann; Bangia et al.; Christensen et al.; Wendin and McNeil; Escalante). These variables contribute to evidence of "fixed effects" in migration, since they differ across years, but not across borrowers. Past research exhibits the influence of economic cycles on migration rates by computing economic capital requirements at different points of the economic cycle. The effect of macroeconomic variables on migration is likely to be more important for active portfolio management than for determining economic capital requirements. In the case of regulators this information can be used to assess the downside risk of portfolios in years of poor economic performance.

Credit risk ratings are becoming more prominent as the emphasis of credit risk management moves from the loan level to the portfolio level. The Basel II Capital Accord highlights the importance of the ratings and their movements in portfolio risk management. While the small size of many agricultural lenders excludes them from the credit risk modeling changes of Basel II, the practice of buying and selling loans to actively manage a loan portfolio is becoming more widespread. In order to participate with larger lenders, smaller lenders may need to have credit risk migration data that the large lenders require. Thus, Basel II may indirectly promote credit risk migration analysis among smaller lenders as well.

Previous Research Findings

The bond market has been thoroughly analyzed with credit risk migration analysis due to the availability of credit risk ratings from Moody's and Standard and Poor's. A key outcome of this work is the empirical evidence for a downgrade momentum among bond rating migrations. In addition bond rating migrations have been shown to be dependent upon the economic cycle (Bangia et al.; Jafry and Schuermann; Nickell, Perraudin, and Varotto).

The simplest method of migration analysis is to gather migrations into a matrix that tracks the likelihood of every possible migration between risk classes. Historically, annual bond and loan migrations tend to be to adjacent classes or in most instances there is no migration at all. Thus, the majority of observations occurs along the diagonal of the matrix for agricultural and bond market data. A migration matrix of bond ratings usually contains 8 or 9 ratings. This is due to the fact that Moody's and S&P use 8 or 9 rating classes. Most recent agricultural studies have used 5 rating classes (Phillips and Katchova; Barry, Escalante, and Ellinger; Escalante et al.; Gloy et al.).

Retention rates (the probabilities if remaining in the same risk classes) among agricultural loans are fairly consistent across the published studies, but those rates are typically lower than the rates reported in the bond portfolio studies (Phillips and Katchova; Barry, Escalante, and Ellinger; Escalante et al.). Given that fewer ratings grades are used in agricultural studies one might expect the retention rates to be higher. Also, those studies use credit scores as proxies for credit risk ratings, and in most cases the migrations are recorded on an annual basis. The year-to-year variations in farm credit scores have been shown to be highly volatile and credit scores that use averages of several years of data tend to more accurately predict future financial performance (Novak and LaDue). A recent study by Gloy et al. uses actual agricultural loan credit risk ratings at commercial banks to produce retention rates that are higher and more comparable to bond rating retention rates.

To determine how a factor influences migration rates, migration matrices must be conditioned on that factor. The economic cycle (as defined by the National Bureau of

Economic Research) was shown to directly influence migration rates using this method (Phillips and Katchova). That study found evidence of a trend reversal in the migration pattern. This result is in contrast with the evidence on bond rating momentum. Thus, there is some evidence that farm loan migrations are different.

Methodology

Migration matrices are used to forecast movements in credit risk in the same manner that a Markov chain works. The primary property of a Markov chain is that the transition (migration) probabilities are constant across time and are only dependent upon the current credit risk classification. The classification in the subsequent period is determined by iteratively applying constant migration probabilities to an initial state. Obviously, this simple method of forecasting is invalid if the migration rates are not constant over time. The dependence of migration rates upon factors other than the current risk rating violates the first Markov property. In that case, migration matrices cannot simply be extrapolated.

Another restriction of the migration matrix method is that all quantitative variables must be transformed into categorical variables. In addition conditioning upon multiple factors can result in a reduction in the degrees of freedom to the point where strong statistical significance is impossible to attain. For example, simultaneously conditioning on two variables with three outcomes creates nine separate migration matrices. If five ratings classes are used there will be forty-five retention rates. This quickly diminishes the number of observations that can be used to calculate the probability of migration. Yet, if one does not condition migration matrices on multiple factors a *ceteris paribus* analysis cannot be achieved. For example, if the business cycle could induce or amplify the influence of previous migrations, finding evidence for or against this effect requires that we analyze the variables simultaneously.

Generalized linear models (GLM) are an alternative way of analyzing migration matrices. The most prominent model types are Logit and Probit. These models can include all three types of factors that influence migration rates. Financial performance, business or life-cycle stage, borrower age, and farm type explanatory variables have been shown to influence agricultural migration rates using GLM (Escalante et al. 2005; Gloy et al.). Macroeconomic variables have only been analyzed in the study by Escalante et al., but those variables were found to be significant predictors of migration. However, the effect of previous migrations has not been studied using GLM. The application presented here provides a point of reference by comparing the results of applying matrix cell-by-cell and GLM analyses to the same data set.

Data

The data is loan level and is provided by four associations in the AgriBank Farm Credit District. The associations cover geographic areas in North Dakota, Wisconsin, Minnesota, and Arkansas. The data include the risk ratings of the loans as well as selected borrower and loan characteristics.

The associations of the AgriBank District began risk rating loans on an expanded 14-point scale during the 4th quarter of 2004. However, for consistency the data used in this study are from the period prior to July 2004, when loans were risk-rated on a 9-point scale (table 1). Even though AgriBank sets the definitions for risk ratings by the associations, each association is responsible for the actual assignment of the risk ratings. Because of possible differences in personnel, management philosophy, etc. one cannot simply assume that the risk rating system is applied uniformly across all associations.

The individual loan observations are semi-annual, beginning in December 1997, and ending in June 2004. This yields a maximum of 14 observations per loan. In total there are 171,683 individual loans with multiple observations. The actual number of observations that have risk ratings is equal to 621,308. The computation of migration rates requires two consecutive observations. In addition, to study the influence of previous migrations each observation must have three years of consecutive credit risk ratings. Imposing these restrictions and requiring observations to have values for every explanatory variable in the model reduces the number of usable observations to 293,358. The majority of unused observations did not have three consecutive years of risk ratings.

Analysis

A Probit model is used and it includes a variable for the direction of migration in the previous period. Migration matrices are also developed, so that the matrices can be compared with the results of the probit analysis. In addition this comparison will provide a reference for comparing past agricultural lending studies that only used one method. The dependent variable is an indicator of the direction of the credit risk rating migration. A downgrade is represented by a value of -1. Remaining in the same credit risk class has a value of zero, and upgrading is assigned a value of 1. Table 2 depicts the frequency and magnitude of migrations in the data set. Explanatory variables used in the analysis include the previous migration, borrower and loan characteristics, and macroeconomic variables.

Previous Migration

The primary goal of this study is to determine what influence, if any, the previous migration of a loan has on the probability of future migrations. Previous upgrades and downgrades are represented by two binary variables. The variables take on a value of 1 when a migration occurred in the previous time period in the appropriate direction. Both variables take the value of 0 to signify that there was no migration in the previous period.

The hypothesis of this paper is that previous migrations will exhibit a momentum pattern. That is upgrades (downgrades) will increase the probability of upgrades (downgrades). This resembles the pattern found among corporate bond ratings migrations, although it is expected to occur for upgrades as well as downgrades. Weak evidence has been found already for upgrade momentum in the higher credit risk ratings of corporate bonds (Lando and Skodeberg; Bangia et al.). The majority of bond migrations occur in low credit risk classes. The downgrade momentum pattern has been found to be the strongest among these low credit risk classes. Agricultural borrowers may exhibit higher credit risk due to their relatively smaller size. Thus, more observations occur in the high credit risk classes where an upgrade momentum is more likely to exist.

A momentum hypothesis implies the belief that one-year credit scores are not representative of actual credit risk ratings. For example, Phillips and Katchova used conditional migration matrices in their analysis. As a consequence, they did not account for other factors that simultaneously affect migration rates.

The initial credit risk rating class is included as an explanatory variable in the Probit equation. By construction loans rated in credit class 1 have a higher likelihood of downgrading than loans in class 8 (those in class nine cannot downgrade). By including these variables we can test for differences associated with the initial risk classification.

Borrower Variables

This set of variables tests the influence of borrower age and/or experience, primary type of agricultural or rural borrower, and geographic location. Borrower age/experience may influence the level of risk tolerance. Due to adverse selection and moral hazard the lender may not be aware of a borrower's true risk tolerance. Loan officers may also be inclined to fund riskier assets for more experienced farmers. Beginning farmer loan programs that lower the cost of borrowing may also influence the significance of age/experience. To avoid multicollinearity problems age/experience is represented as the log of the average of the quantity age plus two times the years of experience**.**

Geographic location and agricultural industry have been shown to be statistically significant predictors in credit scoring models (Turvey and Brown). If these influences are overlooked when the loans are initially risk-rated they may be correlated with subsequent rating migrations. We hypothesize that the probability of migration has a systematic component that reflects the financial prospects of the industry. The variables measuring industry and region are binary variables. The primary source of borrower farm income determines the industry designation of the borrower (table 3). Since the loans of the associations in this study span many states, the loans are allocated into the major farm production regions: Northeast, Lake States, Corn Belt, Northern Plains, Appalachia, Southeast, Delta, Southern Plains, Mountain, and Pacific (U.S. Department of Agriculture).

Since the loan purpose may influence the probability of migration, the loans are classified as operating, intermediate term, real estate, and rural home mortgage loans (table 4). One might hypothesize that real estate loans and mortgages have a lower probability of migration due to the assets that are pledged as security.

Seasoning reflects the length of time since a loan was originated. A seasoned loan is defined as a loan that was originated over 36 months ago and it is treated as a binary variable. A logical explanation for the effect of seasoning relies on the finding that observed retention rates are usually closer to 1 than they are to ½. Given that most loans do not migrate, it is likely that credit risk ratings will not change soon after they are initially determined.

A lender may monitor and underwrite loans of different sizes in different ways.
Thus, the size of loan in this study is defined on two levels. At the borrower level, relationships that are less than $250,000 are classified as small loans, while those greater than $1,000,000 are classified as large loans. Only home mortgages are differentiated based upon size at the loan level. A jumbo mortgage is defined as a loan with principal exceeding $360,000. Jumbo mortgages are classified as large loans. Two binary variables measure whether the loan is small or large.

Macroeconomic Variables

Based on previous findings of the affect of macroeconomic cycles on bond rating migrations, we assume that the same effect should exist in agricultural lending. The percentage change in money supply (we use the M1 measure of money) is included in the regression to account for the availability of financing. The percentage change in M1 is lagged and a positive relationship is expected between movements in the money supply and loan risk migrations.

Farm land is frequently used to collateralize loans and over time changes in its value are reflected in farm borrower balance sheets. Thus, it is likely that changes in farm land values will directly influence credit risk classifications and migration. All of the effect of land value changes may not be positive, since farmers renting land would realize an increase in the expense of renting land as land values rise which may reduce debt repayment capacity and result in a downgrading of credit. Changes in farm land value are measured as changes in the nationwide average value per acre.

Results

Matrix Cell-by-Cell Analysis

Most studies that use matrix analysis to study the influence of previous migrations compare migration rates conditioned upon previous upward, downward, or no change migrations to a matrix of unconditional migration rates. The significance of the differences is determined by a t-test. The same method is used in this study as a benchmark (Table 5). We find that significantly different retention rates of the previous upgrade and downgrade matrices are smaller than the retention rates of the unconditional matrix. In the matrix conditioned on loans that did not previously migrate the significantly different retention rates are greater than the unconditional matrix and a few of the off-diagonal rates are significantly smaller. This type of pattern shows that once a loan does migrate it is more likely to migrate again. Loans that did not previously migrate are less likely to migrate. Some research indicates that a shadow matrix of "excited" state credit risk ratings exist for these loans (Christensen et al.).

Note the migration rates in the previous upgrade matrix that are significantly different from the unconditional migration rates. To the left of the diagonal the rates are smaller, and to the right of the diagonal the rates are greater. This pattern indicates a trend reversal pattern. The trend reversal pattern also appears to exist in the previous downgrade matrix. Here the larger rates are to the left and the smaller rates are to the right of the diagonal. However, a few cells of the matrix in the higher credit risk classes (generally 5-9) do contradict the pattern.

Comparisons to an unconditional matrix show a lender the difference between a naïve and a less naive approach to calculating migration rates. From the lender's perspective the significance of differences between unconditional migration rates and migration rates conditioned on the three possible previous migrations is not the most useful comparison. Rather the lender would naturally compare the differences between migrations conditioned on previous upgrades/downgrades and those conditioned on loans that did not migrate in the previous period. This comparison tells the lender whether the three groups migrate differently (Table 6). The differences between the two comparison approaches are few. In the previous downgrade matrix the pattern supporting trend reversal is weakened. That is, some migration rates to the left of the diagonal (upgrades) become significantly less than the migrations in the "no change" matrix. In addition some migration rates that exhibit downgrades become significantly greater. The case for downgrades increasing the likelihood of future upgrades and reducing the likelihood of future downgrades is weakened.

Probit Model

When accounting for the influence of previous migrations in a regression model it is natural to create two dummy variables that indicate when two of the possible three previous migrations occur. The third possible direction of migration is indicated when the two variables are equal to zero. If upward and downward previous migrations are parameterized into the model their influence is implicitly measured against the migration rates of loans that did not migrate in the previous period. The probit model is:

> Y = f(PREVIOUS MIGRATION, RISKRATING[2-9], Log[AGE_EXP], INDUSTRY, REGION, ASSN[1-3], LOANTYPE[1-3], SEASONED, LOAN SIZE, SMALL, M1PC, FVACRE)

where,

$$Y = \begin{cases} -1 & \text{if previous downgrade} \\ 0 & \text{if no change} \\ 1 & \text{if previous upgrade} \end{cases}$$

The model is an ordered probit model with a three-level response variable. Because of the structure of the response variable the coefficient estimates provide little information about the marginal effects of the variables. In this instance a marginal effect is the amount that the predicted probability of Y changes given a change in an independent variable. Marginal effects of variables in probit specifications are not linear. As a consequence the size of the change in the variable and the values of the other independent variables influence a variable's marginal effect. Most software programs offer a method of calculating the marginal effects of ordered probit and logit models. These programs usually calculate the marginal effects at the means of the independent variables. For binary variables the mean values are never observed and there is only one possible change in value. Furthermore for groups of binary variables there is a direct relationship between the values of the variables. For example if RISKRATING2 has a binary value of 1, RISKRATING[3-8] must all have binary values of zero. Given the specification of this model a more direct approach is preferable.

The most direct approach is to simply compare the probabilities predicted by the estimated equation when a variable is changed by the smallest logical delta. Table 7 shows the marginal effects for all variables. For the groups of binary variables the probabilities will be predicted when one of the variables is equal to 1 and the other variables in the group are equal to 0. All variables outside of the group will be set equal to their means. After the probabilities are computed they can be compared to predicted probabilities calculated when every variable is at its mean value, or the probabilities predicted when the other variables in the same group were equal to 1. Comparing probabilities within the group shows the true marginal effect of the variable. Only differences with the predicted probabilities for the variable excluded from the model can be deemed statistically significant.

Correlations of variables in the model complicate the application of the method. The Arkansas association and the Delta region have a correlation of 0.987. Also, the North Dakota association and the Northern Plains region have a correlation of 0.976. The Minnesota and Wisconsin associations engage in loan participations that geographically spread their lending base. Thus only the Arkansas and North Dakota association variables were allowed into the model, but because of the high correlations no information was lost. However, one is unable to distinguish between the affect of the association and that of the region on migration rates. When the marginal effect is determined for the correlated pair, all other association and region variables must be equal to 0.

Out of this method more matrices are generated to depict the results. These matrices can compare the predicted probabilities across the variables of a group of binary variables for a given response level. There will be three such matrices for each group in this analysis because the response variable has three levels as reported in table 7.

Previous Migration

Table 8 is the matrix of marginal effects for the group of variables representing previous migrations. Negative values indicate that the probability represented by the row is less than the probability represented by the column. Positive values indicate that the opposite is true.

The matrices containing the probability to downgrade, p(-1), and the probability to upgrade, p(1), indicate that a trend reversal pattern does exist. In the p(-1) matrix the probability given a previous upgrade is greater than the probability of downgrading given either a previous downgrade or no migration in the previous period. The exact opposite is true in probability to upgrade matrix. Here the probability to upgrade given a previous downgrade is greater than when the previous migration was an upgrade or a "no change". Together these results show that the probability to migrate in the opposite direction of a previous migration is greater than the probability of migrating again in the original direction. It is also greater than the probability of not migrating at all. This supports the trend reversal pattern found in Phillips and Katchova. A stated hypothesis of this study is that the use of annual credit scores as a proxy for credit risk ratings induces a trend reversal pattern among migration rates. The trend reversal finding of this study does not support the hypothesis.

The matrix that depicts the probability of not migrating to a new credit risk rating also conveys meaningful information. The migration matrices suggested that loans that migrated were more likely to migrate again. Loans that did not migrate were more likely to not migrate in the next period. The negative values for the rows DPM and UPM in the NC column indicates that the probit model agrees with the migration matrix analysis. The results of the probit regression indicate which differences in probability are statistically significant.

In the probit model, the no change (NC) variable was excluded. Thus the significance of DPM and UPM were measured against NC. Because the DPM and UPM variables were significant the differences between these variable's predicted probabilities and NC's predicted probabilities are significant. Furthermore, when the predicted probabilities given DPM or UPM, minus the predicted probability given NC have opposite signs, they can be said to be significantly different for that response level. For p(-1) DPM and UPM are significantly different because their predicted probabilities lie on opposite sides of NC, and they are both significantly different from NC.

The magnitude of the trend reversal is truly large. For the probability of an upgrade the total range of influence from a previous downgrade to a previous upgrade is 3.43 percentage points. To put this number in perspective, the largest unconditional probability of an upgrade (table 5) is from class 8 to class 7 at 18.9%. But, the marginal effect is computed at the average of the variables, and the average initial credit risk rating for the population is 2.83. Thus, the most appropriate comparison values are the largest unconditional upgrade probabilities for classes 2 and 3 at 1.9% and 2.5% respectively.

Initial Risk Rating

The same method is applied to the initial risk rating (Table 9). All risk rating classes are significantly different from risk rating 1, except for risk rating 9. This latter result is due to only a few occurrences of migrations from class 9. The matrices show that the probability of downgrading decreases as you move to credit classes that represent higher risk. The exceptions occur at risk rating 5. However, due to the specification of the probit model, significance can only be inferred for comparisons to risk rating 1.

The probability of upgrading, p(1), increases as you move to credit classes that represent higher risk. The magnitude of the increase is quite large in classes 8 and 9. Lenders spend monitoring effort on these two credit risk classes so the scaling of the magnitudes may be reasonable.

Borrower Specific Variables

The variable L_AGE_EXP which measures the natural log of a weighting of borrower age and experience is statistically significant in the probit model. The marginal effect of the variable was computed for a change of one year in experience, age, or a combination of the two at the mean of the variable (Table 7). An increase of one year at the mean decreases the probability of a downgrade, increases the probability of an upgrade, and decreases the probability of no change.

The REGION variables were tested against the excluded Lake States region. The Appalachian and Southeast regions seem more likely to upgrade. The Southern Plains and Corn Belt regions are more likely to upgrade. The influence of the Northern Plains and Delta regions are intertwined with the lending associations located in those regions.

The INDUSTRY variables were measured against the poultry industry. The Landlord and Timber industries are more likely to upgrade and less likely to downgrade. Rural Residence, Dairy, and Agribusiness loans are more likely to experience a downgrade in credit risk classification, and are also less likely to receive an upgrade.

The LOANTYPE variable was measured against real estate loans. Only intermediate term loans were significantly different. Intermediate term loans are the most likely to downgrade and least likely to upgrade. Home mortgage loans are the least likely to downgrade and the most likely to upgrade.

Seasoned loans were significantly different from unseasoned loans. Seasoning reduces the probability of downgrading and increases the probability of upgrading. Large and small loans were measured against medium size loans. Both variables are significant. Large loans are the most likely to downgrade and least likely to upgrade. Small loans are the most likely to upgrade and the least likely to downgrade. The association that is holding the loan seems to have little influence over the probability of credit risk migration. The association in the Northern Plains region is significantly different from the association located in Wisconsin. The Northern Plains association is more likely to upgrade loans and less likely to downgrade loans. Because of the correlation between the region and the association it is impossible to identify the separate influences of the two factors.

Macroeconomic Variables

Both macroeconomic variables proved to be significant independent variables. The marginal effect of the money supply was measured by a one percentage point change at the average of the semiannual percent change in the money supply in the data. Again the variable is lagged so that the percent change that occurred over the same time period one year ago influences the probability of migration. As the money supply increases the probability of an upgrade decreases only slightly. However, for the same increase the probability of downgrading and remaining in the same credit risk class increases slightly.

The marginal effect of farm value per acre is measured over a change of $1 per acre. For a $1 increase the probability of downgrading decreases slightly while the probability of upgrading is increased slightly. The probability of no migration is unaffected.

Model Prediction

The model is used to predict the within sample migrations. For all loans that experienced a downgraded the model predicted that the loan would not migrate at all. All loans that did not migrate were correctly predicted to not migrate. The model was able to correctly predict three of the loans that upgraded. For all other loans that did upgrade the model again predicted no migration. Given the high retention rates of the data this result is neither surprising nor fatal to the model. The model is not forecasting migrations, but rather the probability of migrating to one of the three response variables. To evaluate the predictive power of the model, one should compare the predicted probabilities for groups of loans that actually migrated to each of the three levels (Table 10).

Table 10 shows that the mean probability of a downward migration is highest for loans that did migrate downward. The downgrade probability is lowest for loans that did migrate upwards. The exact opposite pattern exists among the probability of upgrading. The retention rate is highest for loans that upgraded and lowest for loans that downgraded.

Conclusions and Further Work

The results of the matrix cell-by-cell analysis indicate that there is a significant difference between the matrices conditioned on previous up and down migrations and the matrix containing loans that did not migrate. The pattern of significant differences in the matrices leaves one unsure about the true influence of previous migrations. The probit model shows that indeed a trend reversal pattern does exist. Furthermore the magnitude of the influence of the previous migrations is quite large in comparison to an average loan's probability of migration.

Predicting individual loan migrations remains difficult. The predictive power of the probit is swamped by the naturally large retention rate. At a portfolio level the outlooks are more promising. Here the probabilities to migrate are of primary importance because they determine the number and direction of migrations. The probit model used here is able to improve upon naïve expectations of migration.

This study used semiannual observations. If the observation period is lengthened to a year or longer how does the influence of previous migrations change? One previous attempt to answer this question used the amount of time a bond had been in the current rating as an explanatory variable (Lando and Skodeberg). The use of excited state ratings may also help answer this question. Similarly, only the direction of a migration are considered here. It may be possible to explain the magnitude as well as the direction of a migration.

By re-running the probit model numerous times and excluding different binary variables in each model one can determine the significance between all pairs of binary variables in a group. This information can then be added to the migration probability comparison matrices. The matrix will then show the magnitude of differences between the marginal effects of the explanatory variables and their significance.

The predictive power of the probit model needs to be measured using a more appropriate metric. Once this metric is developed the model can be tested more rigorously. Currently only a with-in sample method has been used.

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Table 1: Risk Rating Definitions

Risk Rating	Definition
1-4	Acceptable
5	Other Assets Especially Mentioned
6	Substandard Viable
7	Substandard Nonviable
8	Doubtful
9	Loss

Table 2: Magnitude of Previous Migrations

PM	Frequency	Cumulative Percent
-6	16	0.01%
-5	63	0.02%
-4	250	0.09%
-3	950	0.3%
-2	3,201	1.1%
-1	12,930	4.4%
0	265,667	90.6%
1	8,279	2.8%
2	1,600	0.5%
3	365	0.1%
4	32	0.01%
5	5	0.002%

Table 3: Loan Industry/Purpose

	Number	Frequency
Crops	96,949	33%
Dairy	85,402	29%
Swine	23,675	8%
Poultry	23,430	8%
Other	23,231	8%
Cattle	22,275	8%
Landlord	12,308	4%
AgriBus	2,019	0.7%
Rural Residence	1,999	0.7%
Horticulture	1,267	0.4%
Timber	803	0.3%
Total	293,358	100%

Table 4: Loan Type

	Number	Frequency
Operating	77,440	26%
Intermediate	87,190	30%
Mortgage	5,613	2%
Real Estate	123,115	42%
Total	293,358	100%

Table 5: Migration Matrices Conditioned on the Direction of the Previous Migration

Unconditional

From\To	1	2	3	4	5	6	7	8	9	#
1	92.3	4.7	2.1	0.7	0.1	0.0	0.0	-	-	39,760
2	1.9	91.5	4.9	1.3	0.3	0.0	0.1	0.0	-	76,032
3	0.5	2.5	91.8	4.3	0.6	0.1	0.2	0.0	-	97,932
4	0.2	0.9	4.8	90.5	2.5	0.5	0.6	0.0	0.0	61,838
5	0.2	0.4	2.9	11.6	78.8	3.2	2.9	-	-	9,366
6	-	0.1	0.9	7.9	2.4	82.0	6.6	0.1	-	3,897
7	-	0.1	0.2	4.1	0.7	1.7	92.8	0.3	-	4,477
8	-	-	1.9	-	-	-	18.9	79.2	-	53
9	-	-	-	-	-	-	100.0	-	-	3
										293,358

No Change — **Compare to Unconditional**

From\To	1	2	3	4	5	6	7	8	9	#
1	**92.7**	**4.5**	2.0	0.6	0.1	0.0	0.0	-	-	37,667
2	**1.8**	**91.9**	**4.7**	1.2	0.3	0.1	0.1	0.0	-	70,467
3	0.4	2.5	**91.9**	4.2	0.6	0.1	0.2	0.0	-	89,508
4	0.2	0.9	4.7	90.6	**2.4**	0.6	0.6	0.0	0.0	54,575
5	0.1	**0.3**	3.0	11.3	**80.0**	**2.7**	2.6	-	-	6,877
6	-	0.2	1.0	8.5	2.1	82.5	**5.8**	-	-	3,007
7	-	0.1	0.3	4.4	0.7	1.9	92.5	**0.2**	-	3,536
8	-	-	-	-	-	-	3.3	**96.7**	-	30
9	-	-	-	-	-	-	-	-	-	-
										265,667

Prev Downgrade — **Compare to Unconditional**

From\To	1	2	3	4	5	6	7	8	9	#
1										-
2	**5.6**	**87.5**	5.7	1.1	**0.1**	-	-	-	-	2,368
3	**1.2**	**4.1**	**90.5**	**3.6**	**0.4**	0.1	**0.1**	-	-	5,101
4	**0.1**	0.8	**6.2**	**88.9**	**3.2**	**0.3**	0.4	-	-	5,809
5	0.3	**0.8**	3.0	12.0	**75.6**	**4.7**	**3.6**	-	-	2,356
6	-	-	0.7	**5.6**	**3.8**	80.0	**9.3**	0.5	-	815
7	-	0.2	-	3.3	0.7	**1.0**	93.9	**0.9**	-	935
8	-	-	4.3	-	-	-	**39.1**	**56.5**	-	23
9	-	-	-	-	-	-	100.0	-	-	3
										17,410

Prev Upgrade — **Compare to Unconditional**

From\To	1	2	3	4	5	6	7	8	9	#
1	**86.4**	**9.8**	2.4	**1.3**	0.1	-	-	-	-	2,093
2	1.8	**86.6**	**9.0**	**2.3**	0.2	-	0.2	-	-	3,197
3	**0.1**	**1.1**	**89.0**	**8.4**	**1.0**	0.2	0.1	-	-	3,323
4	0.1	**0.2**	**2.3**	91.5	**4.4**	0.8	0.8	-	-	1,454
5	1.5	-	0.8	**21.8**	**71.4**	1.5	3.0	-	-	133
6	-	-	1.3	10.7	-	80.0	8.0	-	-	75
7	-	-	-	-	-	-	100.0	-	-	6
8	-	-	-	-	-	-	-	-	-	-
9										-
										10,281

0 Significantly Smaller
0 Significantly Greater

Table 6: Matrices Conditioned on the Direction of Previous Migrations Compared to "No Change"

No Change

From\To	1	2	3	4	5	6	7	8	9	#
1	92.7	4.5	2.0	0.6	0.1	0.0	0.0	-	-	37,667
2	1.8	91.9	4.7	1.2	0.3	0.1	0.1	0.0	-	70,467
3	0.4	2.5	91.9	4.2	0.6	0.1	0.2	0.0	-	89,508
4	0.2	0.9	4.7	90.6	2.4	0.6	0.6	0.0	0.0	54,575
5	0.1	0.3	3.0	11.3	80.0	2.7	2.6	-	-	6,877
6	-	0.2	1.0	8.5	2.1	82.5	5.8	-	-	3,007
7	-	0.1	0.3	4.4	0.7	1.9	92.5	0.2	-	3,536
8	-	-	-	-	-	-	3.3	96.7	-	30
9	-	-	-	-	-	-	-	-	-	-
										265,667

Prev Downgrade

Compare to No Change

From\To	1	2	3	4	5	6	7	8	9	#
1										-
2	**5.6**	**87.5**	**5.7**	1.1	**0.1**	-	-	-	-	2,368
3	**1.2**	**4.1**	**90.5**	**3.6**	**0.4**	0.1	**0.1**	-	-	5,101
4	**0.1**	0.8	**6.2**	**88.9**	**3.2**	**0.3**	0.4	-	-	5,809
5	0.3	**0.8**	3.0	12.0	**75.6**	**4.7**	**3.6**	-	-	2,356
6	-	-	0.7	**5.6**	**3.8**	**80.0**	**9.3**	0.5	-	815
7	-	0.2	-	**3.3**	0.7	**1.0**	**93.9**	**0.9**	-	935
8	-	-	4.3	-	-	-	39.1	**56.5**	-	23
9	-	-	-	-	-	-	100.0	-	-	3
										17,410

Prev Upgrade

Compare to No Change

From\To	1	2	3	4	5	6	7	8	9	#
1	**86.4**	**9.8**	2.4	**1.3**	0.1	-	-	-	-	2,093
2	1.8	**86.6**	**9.0**	**2.3**	0.2	-	0.2	-	-	3,197
3	**0.1**	**1.1**	**89.0**	**8.4**	**1.0**	0.2	0.1	-	-	3,323
4	0.1	**0.2**	**2.3**	91.5	**4.4**	0.8	0.8	-	-	1,454
5	1.5	-	0.8	**21.8**	**71.4**	1.5	3.0	-	-	133
6	-	-	1.3	10.7	-	80.0	8.0	-	-	75
7	-	-	-	-	-	-	100.0	-	-	6
8	-	-	-	-	-	-	-	-	-	-
9										-
										10,281

0 Significantly Smaller

0 Significantly Greater

Table 7: Marginal Effects of Variables Included in the Probit Model

Description	p(-1)	p(0)	p(1)	P > Chi
MEANS	0.0305	0.9202	0.0493	
No Change	0.0304	0.9201	0.0495	Excluded
DPM	0.0232	0.9141	0.0627	**<.0001**
UPM	0.0527	0.9190	0.0284	**<.0001**
Risk Rating 1	0.0970	0.8900	0.0130	Excluded
Risk Rating 2	0.0679	0.9111	0.0210	**<.0001**
Risk Rating 3	0.0502	0.9199	0.0299	**<.0001**
Risk Rating 4	0.0277	0.9185	0.0538	**<.0001**
Risk Rating 5	0.0131	0.8903	0.0967	**<.0001**
Risk Rating 6	0.0205	0.9102	0.0693	**<.0001**
Risk Rating 7	0.0173	0.9036	0.0791	**<.0001**
Risk Rating 8	0.0031	0.7806	0.2163	**<.0001**
Risk Rating 9	0.0000	0.0000	1.0000	0.9871
L_Age_Exp - (.5 years)	0.0305	0.9202	0.0493	**<.0001**
L_Age_Exp + (.5 years)	0.0304	0.9201	0.0495	
Rural Residence	0.0390	0.9220	0.0390	**0.0024**
Dairy	0.0338	0.9214	0.0448	**<.0001**
Swine	0.0303	0.9201	0.0496	0.1275
Agribusiness	0.0337	0.9214	0.0449	0.0696
Crops	0.0300	0.9199	0.0501	0.1520
Other	0.0302	0.9200	0.0498	0.1547
Cattle	0.0277	0.9185	0.0538	0.6722
Horticulture	0.0280	0.9187	0.0534	0.9433
Landlord	0.0242	0.9153	0.0605	**0.0077**
Timber	0.0220	0.9126	0.0654	0.1098
Poultry	0.0282	0.9189	0.0529	Excluded
Southern Plains	0.0431	0.9217	0.0353	**0.0449**
CornBelt	0.0352	0.9217	0.0431	0.1470
Mountain	0.0294	0.9196	0.0511	0.7341
Northeast	0.0277	0.9185	0.0537	0.7980
Pacific	0.0300	0.9199	0.0501	0.9031
Appalachian	0.0230	0.9140	0.0630	0.2251
Southeast	0.0215	0.9119	0.0666	0.1902
Delta				See Arkansas
Northern Plains				See North Dakota
Lake States	0.0309	0.9203	0.0488	Excluded
North Dakota	0.0273	0.9182	0.0546	**<.0001**
Minnesota	0.0308	0.9203	0.0489	0.7102
Arkansas	0.0305	0.9202	0.0493	0.6725
Wisconsin	0.0310	0.9204	0.0486	Excluded
Operating	0.0299	0.9199	0.0502	0.1943
Intermediate	0.0333	0.9212	0.0454	**<.0001**
Real Estate	0.0292	0.9195	0.0514	Excluded
Rural Mortgage	0.0279	0.9186	0.0535	0.4710
Unseasoned	0.0337	0.9213	0.0450	Excluded
Seasoned	0.0286	0.9191	0.0523	**<.0001**
Large	0.0559	0.9176	0.0265	**<.0001**
Medium	0.0351	0.9217	0.0432	Excluded
Small	0.0272	0.9181	0.0547	**<.0001**
M1PC - (.005)	0.0303	0.9201	0.0496	**<.0001**
M1PC + (.005)	0.0307	0.9203	0.0490	
FVACRE - $0.50	0.0306	0.9202	0.0492	**<.0001**
FVACRE + $0.50	0.0305	0.9202	0.0493	

Table 8: Matrix of Differences Between the Marginal Effects of Previous Migrations

Cell* = Predicted Probability of **A** Given **B** - Predicted Probability of **A** Given **C**

*values are in percentage points

P(Downgrade)	Downgrade	No Change	Upgrade
Downgrade	-	0.72	2.95
No Change	0.72	-	2.23
Upgrade	2.95	2.23	-

P(No Change)	Downgrade	No Change	Upgrade
Downgrade	-	0.60	0.48
No Change	0.60	-	0.12
Upgrade	0.48	0.12	-

P(Upgrade)	Downgrade	No Change	Upgrade
Downgrade	-	1.32	3.43
No Change	1.32	-	2.11
Upgrade	3.43	2.11	-

Negative

Positive

Table 10: Predicted Probabilities for each Level of Migration, by the Actual Migration of the Loan

p(-1)	Mean	Minimum	Maximum	Std Dev
Downgrade (-1)	**0.0698**	0.0057	0.2486	0.0326
No Change (0)	0.0553	0.0012	0.2824	0.0273
Upgrade (1)	0.0397	0.0000	0.1663	0.0220

p(0)	Mean	Minimum	Maximum	Std Dev
Downgrade (-1)	0.9034	0.7491	0.9220	0.0207
No Change (0)	**0.9101**	0.6834	0.9220	0.0150
Upgrade (1)	0.9104	0.0000	0.9220	0.0218

p(1)	Mean	Minimum	Maximum	Std Dev
Downgrade (-1)	0.0268	0.0022	0.1593	0.0188
No Change (0)	0.0346	0.0016	0.3154	0.0214
Upgrade (1)	**0.0499**	0.0053	1.0000	0.0332

Table 9: Matrix of Differences Between the Marginal Effects of initial Risk Rating

*values are in percentage points

P(Downgrade)	Risk Rating 1	2	3	4	5	6	7	8	9
Risk Rating 1	-	2.90	4.67	6.93	8.39	7.65	7.97	9.39	
2	2.90	-	1.77	4.02	5.49	4.74	5.07	6.48	
3	4.67	1.77	-	2.25	3.72	2.98	3.30	4.72	
4	6.93	4.02	2.25	-	1.46	0.72	1.04	2.46	
5	8.39	5.49	3.72	1.46	-	0.74	0.42	1.00	
6	7.65	4.74	2.98	0.72	0.74	-	0.32	1.74	
7	7.97	5.07	3.30	1.04	0.42	0.32	-	1.42	
8	9.39	6.48	4.72	2.46	1.00	1.74	1.42	-	
9									-

P(No Change)	Risk Rating 1	2	3	4	5	6	7	8	9
Risk Rating 1	-	2.11	2.98	2.85	0.02	2.02	1.36	10.94	89.00
2	2.11	-	0.88	0.74	2.08	0.09	0.75	13.04	91.11
3	2.98	0.88	-	0.14	2.96	0.97	1.62	13.92	91.99
4	2.85	0.74	0.14	-	2.83	0.83	1.49	13.79	91.85
5	0.02	2.08	2.96	2.83	-	1.99	1.34	10.96	89.03
6	2.02	0.09	0.97	0.83	1.99	-	0.66	12.96	91.02
7	1.36	0.75	1.62	1.49	1.34	0.66	-	12.30	90.36
8	10.94	13.04	13.92	13.79	10.96	12.96	12.30	-	78.06
9	89.00	91.11	91.99	91.85	89.03	91.02	90.36	78.06	-

P(Upgrade)	Risk Rating 1	2	3	4	5	6	7	8	9
Risk Rating 1									
2		-	0.89	3.28	7.57	4.83	5.81	19.53	97.90
3		0.89	-	2.39	6.68	3.94	4.92	18.64	97.01
4		3.28	2.39	-	4.29	1.55	2.53	16.25	94.62
5		7.57	6.68	4.29	-	2.73	1.76	11.96	90.33
6		4.83	3.94	1.55	2.73	-	0.98	14.70	93.07
7		5.81	4.92	2.53	1.76	0.98	-	13.72	92.09
8		19.53	18.64	16.25	11.96	14.70	13.72	-	78.37
9		97.90	97.01	94.62	90.33	93.07	92.09	78.37	-

Negative

Positive