Credit Score Migration Analysis of Farm Businesses:
Conditioning on Business Cycles and Migration Trends

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Abstract

This study examines credit score migration rates of farm businesses. We test whether migration probabilities differ across business cycles. Our results suggest that agricultural credit ratings are more likely to improve during expansions and deteriorate during recessions. We also test whether agricultural credit ratings depend on the previous period migration trends. Our results show that credit score ratings exhibit trend reversal where upgrades (downgrades) are more likely to be followed by downgrades (upgrades).

Key words: business cycle, credit migration, migration trend, path dependence, rating drift, trend reversal

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Migration analysis, a probability-based measurement concept of changes in credit risk, has been used to analyze the effects that business cycles and rating drift have on bond ratings (Bangia et al.; Lando and Skodeberg; and Nickell, Perraudin, and Varotto). Our study conducts similar migration analysis by conditioning migration rates of farm businesses on business cycles and testing for path dependence. Such analysis presents agricultural lenders with valuable insight into modifications to be implemented in their own internal credit risk rating models.

Migration analysis of bond ratings has revealed that transition probabilities are highest for retaining the current rating, decrease as distance between classes increases, and exhibit a higher tendency to downgrade than upgrade.[1] Recent bond studies have shown that transition probabilities are significantly affected by type of industry, geographical location of company, and macroeconomic business cycles (Bangia et al.; and Nickell, Perraudin, and Varotto).

Migration studies have also tested for the presence of rating drift in risk ratings of bonds. A key assumption in migration analysis, known as the Markov property of independence, is that the probability of a bond or loan moving to any state during this period is independent of any outcomes in previous periods (Bangia et al.; and Saunders and Allen). The presence of path dependence implies that the bond's current rating is dependent on previous rating changes, a clear violation of this assumption. Path dependence can be rating drift or momentum, where downgrades (upgrades) are more likely to be followed by downgrades (upgrades), and trend reversal, where downgrades (upgrades) are more likely to be followed by upgrades (downgrades). Studies by Bangia et al. and Lando and Skodeberg found rating drift was present

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[1] A retention rate is defined as the probability of staying in the same credit class.

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in bond ratings; in particular, bonds that downgraded in the previous period were more likely to downgrade in the next period while results on upgrade momentum were less conclusive.

Estimation of migration rates for agricultural loans is complicated by the lack of data on historic loan credit ratings (Barry). In the absence of actual lender loan data, several agricultural finance studies have applied migration analysis to farm-level data. Barry, Escalante, and Ellinger; Escalante et al.; and Katchova and Barry applied migration analysis to farm businesses in Illinois. These studies utilized the Illinois Farm Business Farm Management Association data set, although different time periods were analyzed in each study. Unlike the aforementioned finance studies, these agricultural finance studies estimated a single unconditional transition matrix, without testing whether these migration probabilities differ depending on business cycles and migration trends.

In addition, the previous agricultural finance studies utilized a credit score model as a proxy for credit risk, a tool often employed by agricultural lenders. While a credit score model is useful for estimating borrower creditworthiness, it is generally not the only method employed by lenders in determining credit risk. Lenders analyze financial, non-financial, and character traits of the farm business and operator in internal credit risk rating models. Thus, studies that employ a credit scoring model to measure migration rates of farm businesses, as our study does, may not capture the true credit risk of agricultural loans as well as lenders' internal credit rating tools do.

If rating drift is present in the credit score ratings of farm businesses, there could be serious implications for agricultural lenders. If downgrade momentum is present, then loans that deteriorated in credit quality in previous periods are more likely than other loans to downgrade during future periods, all other factors being the same. Awareness of downgrade momentum would allow lenders to more carefully scrutinize loans that downgraded in credit quality in

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previous periods and better direct monitoring resources towards loans more likely to further deteriorate in the future. On the other hand, if trend reversal is present in agricultural loans, there may not be as serious implications for agricultural lenders. Thus, there is a need to determine if migration rates of farm businesses display path dependence and if so, whether rating drift or trend reversal is present.

This study builds on the previous agricultural finance studies by applying additional migration analysis to farm-level data. Farm-level data for 1985-2002 are utilized from the Illinois Farm Business Farm Management Association to derive annual migration rates based on farmers' calculated credit scores. We calculate a single unconditional transition matrix for the entire sample and test for differences in migration rates by conditioning on the business cycle. In addition, migration analysis is employed to test for a violation of the Markov property of independence or the presence of path dependence in credit score ratings of farm businesses. The following sections explain the measurement approaches, illustrate the theories of credit score migration and trend analysis, address data issues, define the business cycles, present the results, and summarize the conclusions.

Credit Score Migration Rates

Credit score migration analysis considers changes in a farm business's credit quality over time. The changes are summarized across years and farm businesses to produce transition probabilities. Transition probabilities represent the probability of a farm business retaining the same credit score rating or migrating to a different credit score class during a specific time period. Transition probabilities are calculated as follows:

$$(1) \qquad p_{ij} = \frac{n_{ij}}{n_i}.$$

Given that there are n_i farm businesses in a given rating class i at the beginning of the year and that out of this group n_{ij} have migrated from class i to the class j, the one year transition rate is estimated as p_{ij} (Lando and Skodeberg).

In our study, we test whether the Markov property of independence is violated for farm businesses. Path dependence hypothesizes that preceding changes in credit rating hold information about the direction of future rating changes. Rating drift, a form of path dependence, has three characteristics of direction, magnitude, and distance.

To determine if a farm business's previous change in risk rating will influence the change in risk rating from this period to the next period, analysis of three consecutive years of risk ratings is necessary. Consider a risk rating system with five risk classes, $i = 1$ to 5, where class 1 (with credit score = 1) represents the lowest risk farm businesses and class 5 represents the highest risk farm businesses. Assume a farm business's risk rating places it in class i in year t-1, changes to class (i+1) in year t, and then changes to class (i+2) in year t+1. The initial change, from class i to class (i+1), is a downgrade. This initial change, from year t-1 to year t, is the basis for the migration trend measurement and this farm business is placed in the downward trend matrix. If the initial change is an upgrade credit score rating, then the farm business is placed in the upward trend matrix. When the farm business retains its current rating from year t-1 to year t, the farm business is placed in the no trend matrix. If a downgrade momentum is present in the sample, an initial downgrade in credit quality would be followed by another downgrade from year t to year t+1. The opposite is true of upgrade momentum: an upgrade in risk rating would be followed by another upgrade in credit quality. The other case of path dependence, trend reversal, will have upgrades more likely to be followed by downgrades and less likely to be followed upgrades, and vice versa. Figure 1 is a simplified illustration of the

patterns of upgrades and downgrades over the required three-year period.

Conditional Credit Score Migration

Previous agricultural finance studies assumed that transition probabilities are the same across all years, independent of factors such as business cycles and migration trends, while our hypothesis is that transition probabilities differ across business cycles and migration trends. To test this hypothesis, we first calculate the unconditional transition probabilities, p_{ij}, according to equation (1). We then calculate conditional transition probabilities, p_{ij}^c, for the business cycles and migration trends. Transition probabilities are calculated separately for farm businesses during the years of expansion and recession, which produces a conditional transition matrix for each cycle. Our hypothesis for testing for the effect of business cycle is as follows:

(2) $H_0: p_{ij} = p_{ij}^c(\text{expansion}) = p_{ij}^c(\text{recession})$

    $H_a: p_{ij} \neq p_{ij}^c(\text{expansion})$ or $p_{ij} \neq p_{ij}^c(\text{recession})$.

In the case of migration trends, there are three conditional matrices, downward trend, upward trend, and no trend, based on the initial change in a farm business's credit rating. Our hypothesis for testing for the violation of the Markov property of independence is:

(3) $H_0: p_{ij}(\text{upgrade}) = p_{ij}^c(\text{upgrade}|\text{upgrade}) = p_{ij}^c(\text{upgrade}|\text{downgrade}) = p_{ij}^c(\text{upgrade}|\text{no trend})$

    H_a: At least one $p_{ij}^c \neq p_{ij}$.

To determine if the unconditional transition matrix is different from the conditional business cycle matrices and migration trends matrices, we compute t-statistics equal to the difference between the conditional probabilities and the unconditional probabilities divided by the standard errors of the conditional probabilities. We follow Nickell, Perraudin, and Varotto in calculating the standard errors of the conditional probabilities and the t-statistics as follows:

(4) $se(p_{ij}^c) = \sqrt{\dfrac{p_{ij}^c(1 - p_{ij}^c)}{n_i}}$, and

(5) $t = \dfrac{p_{ij} - p_{ij}^c}{se(p_{ij}^c)}$.

If these probabilities are significantly different via the t-statistics test, the unconditional matrix is not the most accurate measure of credit migration and conditional migration analysis should be employed. In the case of path dependence, significantly different t-statistics imply that the Markov property of independence is violated for the specific sample period. If path dependence is not present in credit migration of farm businesses, a pattern of systematic upgrades or downgrades will not be observable in the transition probabilities.

While Nickell, Perraudin, and Varotto evaluate differences between transition matrices using cell-by-cell t-test comparisons, two finance studies (Jafry and Schuermann; and Schuermann and Jafry) suggest an alternative approach where matrices are compared using an overall singular value measure. Transition matrices are diagonally-dominant (with high probabilities concentrated on the diagonal) which implies little migration. Since we are interested in the amount of migration, a mobility matrix $\tilde{P}$ is calculated by subtracting the identity matrix I from the transition matrix P (with elements p_{ij}):

(6) $\tilde{P} = P - I$.

The identity matrix represents a static matrix with no migration, thus the mobility matrix represents only the dynamic part of the original transition matrix. Using the mobility matrix, we calculate the singular values of $\tilde{P}$,

(7) $S(\tilde{P}) = \sqrt{eig(\tilde{P}'\tilde{P})}$,

where $eig(\text{g})$ are the eigenvalues of a matrix. The average of the singular values of the mobility

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matrix, $\overline{S(\tilde{P})}$, approximates the average probability of migration across all credit classes (Jafry and Schuermann). The unconditional and conditional matrices can be compared using the singular value metric:

(8) $m(\tilde{P},\tilde{P}^c) = \overline{S(\tilde{P})} - \overline{S(\tilde{P}^c)}$.

We need to know if the singular value metric $m(\tilde{P},\tilde{P}^c)$, based on the overall difference in the probabilities between the two matrices, is significantly different from zero. We use 1,000 bootstrap samples from the original data to estimate a confidence interval for the metric. We will reject the null hypothesis that the conditional and unconditional matrices are equal if zero is outside the 95% confidence interval for the singular value metric.

Measurement Approaches

In order to calculate migration rates, one must first classify farm businesses by credit worthiness using a risk rating instrument. Bonds are assigned risk rating categories by the rating companies such as Moody's and Standards and Poor's; thus, bonds transition between rating categories as they are reevaluated by the rating companies.

Zech and Peterson used linear and logistic analysis to decipher the factors that predict actual farm profitability and debt repayment ability of Minnesota farms. They found the rate of asset turnover and family living expenses to be strong predictors of farm performance and the debt-to-asset ratio to be a strong predictor of repayment ability over several time periods. Barry, Escalante, and Ellinger used measurements of profitability, repayment capacity, and a credit scoring model to classify farm businesses by credit risk. They found the credit score approach produced higher retention rates than the other classification approaches. Credit scoring models provide a more comprehensive evaluation of credit worthiness than a single measurement, by

incorporating multiple financial factors into a composite index of credit risk, including measures of profitability and repayment capacity.

In this study, farm businesses are assigned credit scores based on the term loan credit scoring model developed by Splett et al. This model utilizes financial ratios recommended by the Farm Financial Standards Task Force (FFSTF) as explanatory variables, including one measure each of liquidity, solvency, profitability, repayment capacity, and financial efficiency, to sort farms into five uniform risk rating classes. Class 1 contains the lowest risk borrowers while class 5 represents the highest risk borrowers.[2] The credit score used in this study differs from Splett et al. in that it defines new interval ranges for the repayment capacity measure since the intervals defined by Splett et al. resulted in heavy concentration of observations in the first class. The use of the credit score as a measurement tool and the use of the new interval ranges for the repayment capacity measure are consistent with the practices of previous agricultural finance studies (Barry, Escalante, and Ellinger; Escalante et al.; and Katchova and Barry).

While modern capital management studies (Barry; and Basel Committee on Banking Supervision) suggest that more than five classes is ideal for measuring credit risk, there are pros and cons to such classification systems. More classes suggest increased homogeneity of loans within each class. On the downside, however, more classes lead to an increase in the probability of misclassification of loans, to a decrease in the retention rates, and can be hard to implement.[3]

For our purposes, migration analysis is measured by year-to-year transition probabilities. This is consistent with the finance literature (Bangia et al.; Lando and Skodeberg; and Nickell,

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[2] This 5-class credit scoring model does not include a class for farm businesses in default. Loans are often classified as in default when payments are 90 days or more past due, a variable that is unknown in our sample. Because farm-level data is utilized, and not lender loan data, the only measure of default available in the data is insolvency. Similarly to Katchova and Barry, we can define a default class for insolvent farm businesses and repeat the analysis. These results (available from the authors upon request) are almost identical to the results reported here.

[3] Analysis of a ten class credit scoring model was performed by splitting each of the existing five classes in half. Results were generally consistent with the findings of the five-class analysis presented in this paper but are not included in the paper (available from authors upon request).

Perraudin, and Varotto). Other agricultural finance studies (Barry, Escalante, and Ellinger; Escalante et al.; and Novak and LaDue) have also used three-year moving average measurements, which smooth a portion of the annual random movements in credit risk outcomes in order to differentiate the systematic movements from the random movements. In order to test for the effects of business cycles and the presence of path dependence, we need to capture annual changes in credit quality since both business cycles and migration trends are defined on an annual basis. Therefore, our study's objectives limit the measurement of transition probabilities to one year.

Data Issues

This study employs annual farm-level data from the Illinois FBFM data set for 1985 to 2002. The FBFMA has annual membership of more than 6,500 farms; however, only a portion of these farms pass the field staff's rigorous process of certification of financial records.

The initial unconditional transition matrix is developed based on farm businesses with a minimum of two consecutive years of participation and is compared to conditional transition matrices of the business cycles to test the effects of such cycles. To test for path dependence, an unconditional transition matrix is developed using only those farm businesses with a minimum of three consecutive years of participation. By selecting two consecutive years of data for the cycles analysis and three consecutive years of data for the migration trend analysis, we introduce survival bias.[4] This problem, however, is unavoidable given the measurement requirements of our study. Analysis of summary statistics for the two year sample and three year sample show the farms in each sample are similar in characteristics. The means and standard deviations for characteristics including assets, liabilities, leverage, tenure, and total acres farmed are very

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[4] Exclusion of a default class implies that all farm businesses "survive" in the migration analysis.

similar. In addition, the percentage of downgrades, upgrades, and retentions in each sample is identical at 25, 23, and 52%. Based on these statistics, it seems the farm businesses that survive for at least three years have similar characteristics to those that survive a minimum of two years.

Earlier, we cited finance literature (Bangia et al.; and Nickell, Perraudin, and Varotto) that suggests transition probabilities should be based on several conditioning factors, such as location of borrower, type of borrower, and business cycle. Nickell, Perraudin, and Varotto found the location of the bonded company or borrower to be of significance when they considered bonds of companies in different countries. Since the entire sample in our study is located in the state of Illinois, this analysis is not included in our study.

The same study also found bond transition probabilities differed across industries. While this hypothesis could easily be applied to agriculture by grouping farm businesses by type of production, our data set is limited in this nature. Illinois farms are predominantly involved in grain production, while livestock farms, diversified farms, and specialty farms make up a small portion of aggregate production. These trends are represented in the FBFMA data set where grain farms represent 86% of farms, while hog production is second at 7%, and dairy production third with 3%. The composition of our sample of mostly grain farms prevents us from conditioning migration analysis by type of production of farm business.[5]

Business Cycle Definitions

Bangia et al.; and Nickell, Perraudin, and Varotto found year-to-year migration rates of bonds differed depending on corresponding national business cycles. Nickell, Perraudin, and

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[5] Previous agricultural finance studies (Barry, Escalante, and Ellinger; Escalante *et al.*; and Katchova and Barry) utilizing the same data source (Illinois FBFM) analyzed migration rates for all farms, not just grain farms. In addition, migration analysis results are similar when our sample is restricted to grain farms (results available from authors upon request). Thus, our migration analysis includes all farm types, though we recognize the composition of farms in our sample is a limitation of this study.

Varotto studied migration analysis of international bonds by business cycle. They compared annual GDP levels across applicable countries to averages in order to determine the business cycle of each bond for each year. Bangia et al. defined the business cycle based on the definitions reported monthly by the National Bureau of Economic Research (NBER).

Bangia et al. suggest that the state of the economy, or business cycles, can serve as a proxy for measurement of the systematic risk of a firm's asset portfolio. In addition, Pederson, Stensland, and Fischer suggest macroeconomic policies directly and indirectly affect the agricultural industry, primarily through interest rates and exchange rates. Exchange rates affect exports and imports of agricultural products, while interest rates influence loan terms of agricultural loans. The underlying correlations between exchange rates, interest rates, and agricultural credit risks are driven by macroeconomic policies, while changes in economic cycles serve as indicators of shifts in the underlying macroeconomic policies and reflect changes in exchange rates and interest rates. For example, Bjornson found that expected lands returns were significantly affected by the business cycle effects of changing capital market risk premia and discount rates for the period 1961-1990. Results from this study suggest that agricultural asset performance and valuation should account for macroeconomic conditions and business cycles in addition to agricultural sector conditions.

In this study, we follow Bangia et al. and define the business cycle as *expansion* and *recession* based on the published reports of NBER. According to the NBER, the United States' economy was in expansion during 1985 through 1989 and 1992 through 2000 while sustaining recessions from 1990-1991 and 2001. Though NBER has yet to release a report on the business cycle(s) experienced in 2002, we classify 2002 as a recession due to possible lag effects of the 2001 recession. For example, migration rates for changes in farm business's credit score from

1988 to 1989 are included in the expansion cycle matrix, while changes from 1989 to 1990 are included in the recession cycle matrix.

Migration Results

The transition probabilities averaged across the full sample are exhibited in table 1. Similarly to previous agricultural finance studies (Barry, Escalante, and Ellinger; Escalante et al.; and Katchova and Barry), we find retention rates for class 1, 2, and 3 display the highest transition probabilities but are substantially lower than those exhibited by bond ratings. Retention rates, displayed along the diagonal of the matrix, represent the probability of a farm business remaining in the same credit score class for concurrent periods. The highest transition probability is 75.48%, signifying the probability of class 1 farm businesses retaining their credit score of 1 in the next period.

The transition probabilities usually exhibit greater tendency to move one class away from the current class in both directions and lower tendency to move more than one class from the current class. For example, in table 1 we can see that the likelihood of a farm business currently in class 3 migrating to class 4 is 16.85%, but the likelihood of the same class 3 farm business moving to class 5 is only 9.87%. Generally, the probabilities of a farm business migrating to a "near" class are higher than the probabilities of migrating to a "far" class. The singular value metric matrix, unlike the cell-by-cell comparisons, takes into account near versus far migration.

Business Cycle Results

We examine the results from the business cycle matrices in table 2. Based on two-tail tests with 95% confidence level, we find 14 of 25 transition probabilities observed during the expansion

cycle and 18 of 25 transition probabilities observed during the recession cycle are significantly different from those of the unconditional matrix, as shown in table 1. Six of the ten retention rates are significantly different from unconditional retention rates. The numbers in parentheses below the transition probabilities show the differences in the transition probabilities between the business cycle matrix and the unconditional matrix.

During the expansion cycle, some transition probabilities below the diagonal of retention rates in the matrix are higher than the unconditional matrix while those above the diagonal are lower. For example, the likelihood of a farm business currently in class 2 migrating up to class 1 in the next period is 2.69% higher in the expansion matrix than the unconditional matrix. The opposite pattern is exhibited in recession cycle matrix. Here, the likelihood of a farm business currently in class 2 migrating down to class 3 is 4.19% greater in the recession matrix than the unconditional matrix.

Another striking result is the fluctuation in the retention rate of class 5, the highest risk class, across business cycles and the unconditional matrix. During expansion, the retention rate is 7.22% significantly lower than the unconditional retention rate. During recession, however, the retention rate for class 5 is 21.68% significantly higher than the unconditional retention rate. These results suggest farm businesses are more likely to improve during the expansion cycle and more likely to remain in high credit risk classes during recession. In particular, farm businesses in the high risk classes 4 and 5 are much more likely to retain or worsen their financial position and less likely to improve their financial position during recessions.[6] These farm businesses are more likely to improve their financial position during expansion periods by migrating away from the high risk classes.

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[6] An increase in concentration in classes 4 and 5 during the recession cycle could be due to increases in default. Near-default farms would most likely be classified as high risk before exiting the sample.

Our results are consistent with those of previous finance studies, which studied significant differences in cell-by-cell transition probabilities. Nickell, Perraudin, and Varotto found that transition probabilities of bonds exhibited a higher tendency to upgrade during a business cycle peak (expansion) but a higher tendency to downgrade during a business cycle trough (recession). Bangia et al. also found the same pattern in transition probabilities of bonds, where bonds exhibited a greater tendency to improve during a U.S. expansion cycle but a greater tendency to deteriorate during a U.S. recession cycle. The results of Bangia et al. are especially relevant in comparison to our results, given that both studies utilized the NBER cycle definitions for the business cycle.

In addition, matrices for the expansion and recession cycles were each compared to the unconditional matrix using the singular value metric. We calculated the mobility matrices by subtracting the identity matrix from the original matrices and estimated the singular values as the average of the eigenvalues of the mobility matrices. We used a bootstrap with 1,000 replications to calculate 95% confidence intervals for the difference between the singular values for the unconditional matrix and those of the expansion (or recession) matrix. The confidence intervals turned out to be (-0.0273, -0.0269) for the difference between the unconditional and the expansion matrix and (0.0602, 0.0613) for the difference between the unconditional and the recession matrix. Because zero is outside of these confidence intervals, we conclude that overall the unconditional matrix is significantly different from the expansion and recession matrices. These results confirm the cell-by-cell conclusions that migration probabilities differ significantly in expansion and recession cycles.

Our results suggest farm businesses exhibit a greater tendency to upgrade when the national economy is in expansion and to downgrade when the economy is in recession than if we

do not condition on the business cycle. Furthermore, the statistical significance of these results suggest the unconditional transition probabilities produce misleading results and supports the hypothesis that macroeconomic conditions, as represented in this study by the business cycle, do affect the financial performance of farm businesses. Moreover, results lead us to conclude agricultural lenders should include macroeconomic factors, such as the business cycle, in migration analysis in order to minimize credit risk in their agricultural loan portfolios. Additionally, agricultural lenders have to be concerned about deteriorating loan quality during recession times.

Migration Trend Results

The full sample transition matrix is presented in table 3. A new unconditional matrix must be calculated to test for path dependence because of the minimum requirement of three consecutive years of data, as opposed to table 1, which is based on a minimum requirement of two consecutive years.

Table 4 shows the transition probabilities for downward trend, no trend, and upward trend, with the difference in transition rates between the trend matrix and the unconditional matrix shown in parentheses below. Farm businesses in the downward trend (upward trend) matrix experienced downgrades (upgrades) during the previous period of migration analysis, while those in the no trend matrix retained their credit score rating during the previous period of migration measurement. A two-tailed test with 95% confidence is employed to determine if any of the trend transition probabilities differ from that of the full sample.

The first noteworthy result is the number of significant probabilities present in the no trend matrix. In previous studies, the no trend matrix exhibited little significance when rating

drift was present (Bangia et al.). Thirteen out of twenty-five transition probabilities exhibited

rates significantly different from that of the unconditional matrix. The retention rate of class 1,

81.45%, is 5.55% higher than the unconditional matrix, while the retention rate for class 5,

48.55%, is 16.00% higher than that of the unconditional matrix. In fact, all of the retention rates

are significantly higher than the unconditional retention rates. The significance found in the no

trend matrix implies that a significant number of farm businesses maintain their credit score

rating over a consecutive time period. The fact that farm businesses exhibiting no trend in the

previous period are more likely to continue to retain their rating supports our hypothesis that the

Markov property of independence is violated in our sample.

Secondly, the significant probabilities in the downward trend and upward trend matrices

do not exhibit a pattern of rating drift, or momentum, as has been found in bond studies (Bangia

et al.; and Lando and Skodeberg). The number of significant probabilities, however, indicates

that the Markov property of independence is violated. Instead of rating drift, the significant

transition probabilities in the downward and upward trend matrices exhibit a pattern of trend

reversal. For example, the transition probabilities for class 3 in the downward trend matrix are

higher in lower risk classes and lower in the higher risk classes than the full sample. The

probability of downgrading from class 3 to class 4 following a downgrade is 5.87% lower than

the unconditional, while the probability of upgrading from class 3 to class 2 following a

downgrade is 10.28% higher than the unconditional. Thus, farm businesses in class 3 that

experienced a downgrade in credit quality last period are more likely to upgrade and less likely

to further downgrade in credit quality over the next period.

The opposite pattern is represented in the upward trend matrix. The probability of

upgrading from class 3 to class 2 following an upgrade is 8.82% lower than the unconditional,

while the probability of downgrading from class 3 to class 4 is 10.45% higher than the unconditional. This demonstrates a pattern of trend reversal, whereby farm businesses are more likely to downgrade than upgrade in credit quality following an upgrade in the previous period.

As with the business cycle, we used the overall singular value metric to test whether the transition matrices conditioned on previous trends were significantly different from the unconditional transition matrix. The confidence intervals for the difference between the unconditional matrix and the downward trend, no trend, and upward trend matrices were (-0.0968, -0.0840), (0.0895, 0.0908), and (-0.0730, -0.0626), respectively. These results show significant differences between the probabilities in the unconditional and conditional matrices. In other words, we find that credit migration depends on the previous period trends.

Based on our results, the Markov property of independence is violated in our sample and path dependence is found to exist. While our results suggest that path dependence is present, rating drift is not the form of path dependence present in the sample. Instead, our results suggest that trend reversal of credit score ratings is present in our sample. The transition probabilities of the downward trend matrix are higher for migrating to lower risk classes, implying a downgrade in credit quality last period would more likely result in an upgrade in credit quality over the next period in comparison to an unconditional upgrade. The opposite pattern is present in the upward trend matrix, where the transition probabilities for migrating to higher risk classes are higher, implying an upgrade in credit risk last period would be more likely to be followed by a downgrade next period.

Bond ratings are determined by rating agencies, which utilize a complex, quantitative and qualitative judgmental process to rate bonds; however, in our study, farm businesses are measured by a credit scoring model. Agricultural lenders, though, use their own individualized

internal risk rating models, similar to those of bond rating agencies, to risk rate agricultural borrowers. While agricultural lenders' internal models may include a credit scoring model, such a model is likely not their only risk rating tool. In addition, the rating drift studies utilized data on bond ratings, but our study utilizes farm-level data instead of loan-level data. Analysis of path dependence in agricultural borrowers may produce different results than that of our study of farm businesses. Based on these distinct differences, we can not assess whether or not rating drift or trend reversal is present in agricultural borrowers, despite the fact that we find trend reversal present in our sample of farm businesses.

Summary and Concluding Remarks

The results of this study suggest agricultural lenders should employ credit risk migration analysis that determines transition probabilities across business cycles in order to fully evaluate the credit risk held in their agricultural loan portfolios. We have shown transition probabilities differ significantly across these business cycles when compared to the unconditional migration probabilities, the traditional migration analysis employed by lenders. In particular, the results from the cycles show farm businesses exhibit a higher tendency to downgrade (upgrade) than upgrade (downgrade) during recessions (expansions). Our results are consistent with the results of finance studies (Bangia et al.; and Nickell, Perraudin, and Varotto), which found that bond ratings exhibit a higher tendency to downgrade in recession and upgrade in expansion.

We also found that the Markov property of independence is violated in our sample and that trend reversal of credit score ratings is present in farm businesses. Our finding of trend reversal is in contradiction to the downward momentum found in bond ratings by finance studies (Bangia et al.; and Lando and Skodeberg). Based on our sample and measurement process, we

can not determine whether or not trend reversal or rating drift is present in agricultural borrowers, though this study finds trend reversal to be present in a sample of farm businesses.

Further studies are warranted to determine if transition probabilities differ significantly across types of agricultural production and geographical locations of farm businesses and agricultural borrowers. Just as Splett et al. determined lenders should develop credit score models for borrowers based on different structural characteristics, including loan structure and type of production, lenders need to condition migration analysis based on many of these same structural characteristics in order to better assess agricultural borrowers' credit risk. The lack of diversity amongst farm types in our data set prevented us from analyzing migration analysis differences across farm types. A national data set or a regional data set encompassing multiple states would be most appropriate for such studies. In addition, our findings should be compared to studies that utilize lender loan-level data to verify our results.

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Figure 1. Simplified Illustration of Migration Trends

$t - 1$ t $t + 1$

i-2   Upgrade Momentum

Upgrade

i-1

Upgrade

i Trend Reversal

Score = i

Downgrade

i+1

Downgrade

i+ 2   Downgrade Momentum
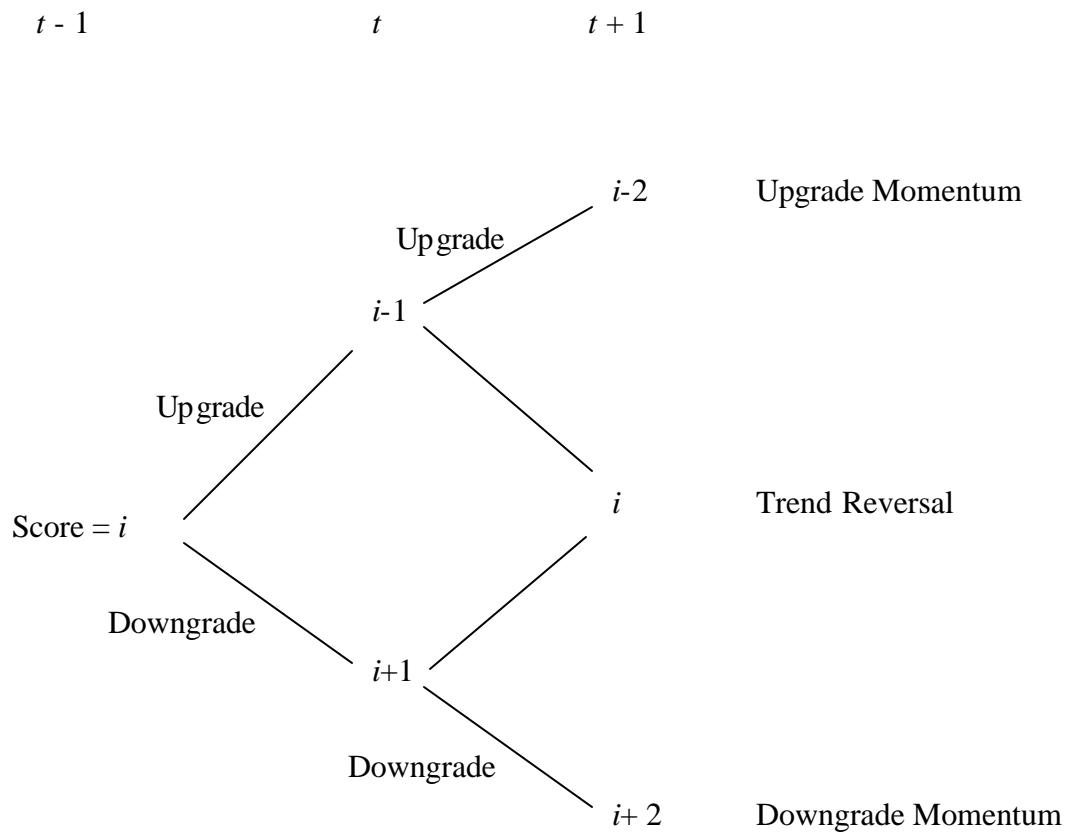
Table 1. Unconditional Migration Probabilities

	Next Year					Farm Obs.
	Class 1	Class 2	Class 3	Class 4	Class 5	
Current Year						
Class 1	75.48	16.78	6.19	1.43	0.12	5,941
Class 2	20.91	44.13	22.85	9.19	2.92	4,625
Class 3	7.71	23.25	42.33	16.85	9.87	4,125
Class 4	4.12	19.65	33.15	27.66	15.42	1,822
Class 5	0.48	11.00	35.22	21.72	31.58	1,045

The numbers in the table indicate the probability of moving from class i in the current year to class j in the next year, expressed as a percentage.

The sample size is based on two consecutive years of data.

This matrix is compared to the business cycle-conditioned migration matrices.

Table 2. Business Cycle-Conditioned Migration Probabilities

	Next Year					
	Class 1	Class 2	Class 3	Class 4	Class 5	Farm Obs.
Current Year						
Expansion						
Class 1	77.12*	16.05	5.42*	1.27	0.14	4,319
	(1.64)	(-0.73)	(-0.77)	(-0.16)	(0.02)	
Class 2	23.60*	44.62	21.28*	8.29	2.20*	3,364
	(2.69)	(0.49)	(-1.57)	(-0.90)	(-0.72)	
Class 3	9.22*	25.58*	41.67	14.66*	8.88	2,940
	(1.51)	(2.33)	(-0.66)	(-2.19)	(-0.99)	
Class 4	5.17	23.91*	33.96	24.14*	12.82*	1,334
	(1.05)	(4.26)	(0.81)	(-3.52)	(-2.60)	
Class 5	0.64	13.78*	39.03*	22.19	24.36*	784
	(0.16)	(2.78)	(3.81)	(0.47)	(-7.22)	
Recession						
Class 1	71.09*	18.74*	8.26*	1.85	0.06	1,622
	(-4.39)	(1.96)	(2.07)	(0.42)	(-0.06)	
Class 2	13.72*	42.82	27.04*	11.58*	4.84*	1,261
	(-7.19)	(-1.31)	(4.19)	(2.39)	(1.92)	
Class 3	3.97*	17.47*	43.97	22.28*	12.32*	1,185
	(-3.74)	(-5.78)	(1.64)	(5.43)	(2.45)	
Class 4	1.23*	7.99*	30.94	37.30*	22.54*	488
	(-2.89)	(-11.66)	(-2.21)	(9.64)	(7.12)	
Class 5	0.00	2.68*	23.75*	20.31	53.26*	261
	(-0.48)	(-8.32)	(-11.47)	(-1.41)	(21.68)	

* denotes significance at a 95% confidence level (two-tailed).
The numbers in parentheses indicate differences from the unconditional matrix in table 1.
This sample size is based on two consecutive years of data.
Expansion Cycles: 1985-1989, 1992-2000.
Recession Cycles: 1990-1991, 2001-2002.

Table 3. Unconditional Migration Probabilities

	Class 1	Class 2	Class 3	Class 4	Class 5	Farm Obs.
			Next Year			
Current Year						
Class 1	75.90	16.92	5.74	1.37	0.07	4,096
Class 2	20.74	45.18	22.42	8.97	2.69	3,154
Class 3	7.57	23.89	42.68	17.02	8.85	2,826
Class 4	4.09	18.57	34.07	28.48	14.79	1,271
Class 5	0.00	11.27	33.80	21.97	32.55	719

The sample size is based on three consecutive years of data.
This matrix is compared to the trend-conditioned migration matrices.

Table 4. Trend-Conditioned Migration Probabilities

Current Year	Next Year					Farm Obs.
	Class 1	Class 2	Class 3	Class 4	Class 5	
Downward Trend						
Class 1	-	-	-	-	-	
Class 2	41.14*	40.73*	11.30*	6.14*	0.70*	717
	(20.4)	(-4.45)	(-11.12)	(-2.83)	(-1.99)	
Class 3	17.40*	34.17*	32.50*	11.15*	4.79*	960
	(9.83)	(10.28)	(-10.18)	(-5.87)	(-4.06)	
Class 4	5.29	22.12*	34.62	24.64*	13.34	832
	(1.20)	(3.55)	(0.55)	(-3.84)	(-1.45)	
Class 5	0.55	13.00	37.73	21.25	27.47*	546
	(0.55)	(1.73)	(3.93)	(-0.72)	(-5.08)	
No Trend						
Class 1	81.45*	12.50*	5.28	0.73*	0.03	3,143
	(5.55)	(-4.42)	(-0.46)	(-0.64)	(-0.04)	
Class 2	17.69*	48.82*	22.63	8.08	2.79	1,436
	(-3.05)	(3.64)	(0.21)	(-0.89)	(0.10)	
Class 3	3.11*	20.61*	50.97*	15.81	9.50	1,189
	(-4.46)	(-3.28)	(8.29)	(-1.21)	(0.65)	
Class 4	2.33*	15.28	30.23	37.54*	14.62	301
	(-1.76)	(-3.29)	(-3.84)	(9.06)	(-0.17)	
Class 5	0.00	5.78*	21.39*	24.28	48.55*	173
	(0.00)	(-5.49)	(-12.41)	(2.31)	(16.00)	
Upward Trend						
Class 1	57.61*	31.48*	7.24	3.46*	0.21	953
	(-18.29)	(14.56)	(1.50)	(2.09)	(0.14)	
Class 2	10.49*	43.16	30.07*	12.19*	4.00*	1,001
	(-10.25)	(-2.02)	(7.65)	(3.22)	(1.31)	
Class 3	1.48*	15.07*	42.54	27.47*	13.44*	677
	(-6.09)	(-8.82)	(-0.14)	(10.45)	(4.59)	
Class 4	0.72*	4.35*	39.13	31.88	23.91*	138
	(-3.37)	(-14.22)	(5.06)	(3.40)	(9.12)	
Class 5	-	-	-	-	-	

* denotes significance at a 95% confidence level (two-tailed).

The numbers in parentheses indicate differences from the unconditional matrix in table 3.

The sample size is based on three consecutive years of data.