Credit Risk Migration Analysis of Cooperatives

by

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Abstract

Cooperatives struggled financially in the early 2000s because profitability declined. In 2002, Agway and Farmland Industries filed for Chapter 11 bankruptcy. Since then, bankruptcy events have been few, and cooperative profitability has rebounded. Credit risk is of particular importance to lenders, managers, and directors. Lenders are primarily concerned about their counterparty exposure to cooperatives while cooperatives are concerned about meeting their debt obligations and distributing patronage to their members. Conceptualizing the expected credit risk behavior of cooperatives over time and responses to exogenous favorable and adverse factors offer useful insight to cooperative managers.

The objective of this thesis is to assess the historical evolution of agricultural cooperative credit risk. This will be done by studying the credit rating migration behavior of cooperatives using Markov chains. This research uses proprietary cooperative financial statement data of 155 cooperatives spanning from 1996 to 2014. The Credit Metrics component of Moody's Global Agricultural Cooperatives Industry Rating Methodology is used to assign annual credit ratings. Unconditional transition probabilities and probabilities conditioned on the type of cooperative, the state of the economy, and the performance of the agricultural sector are estimated to compare differences in migration behavior. Non-Markovian behavior and time-heterogeneity are also examined.

Cooperatives are more likely to experience a change in credit rating in the next period than remain unchanged. When the direction of the rating change is considered, cooperatives are more likely to be upgraded than downgraded. However, more annual instances of downgrades exceeding upgrades are observed across the sample. There are numerous instances where downgrades and upgrades span multiple rating classes. This occurs because cooperatives are

often small and not diversified enough to withstand adverse challenges to their operations. Rating history impacts the direction of the subsequent rating change. Cooperatives that were previously unchanged in the prior period are more likely to retain their rating in the next, while those previously upgraded are more likely to be downgraded, and those previously downgraded are more likely to be upgraded. We find that the rating process does not follow a first-order Markov chain.

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Chapter 1 - Introduction

1.1 Cooperative Credit Risk

The beginning of the new millennium saw the continuation of the decline in profitability of agricultural cooperatives. According to cooperative managers, the notable issues that plagued cooperatives during that period included the decline in commodity prices, the state of the agricultural economy, operational challenges, and increased costs (Gray & Kraenzle, 2002). In addition, inter-cooperative coordination costs had risen, members were increasingly more heterogenous, and the industry had become more competitive (Bond, 2006). Many of the aforementioned drivers were industry effects, meaning they impacted all cooperatives belonging to the farm supply and grain marketing industry (Boyd, Boland, Dhuyvetter, & Barton, 2007).

In 2002, Agway and Farmland Industries filed for Chapter 11 bankruptcy. Since then, bankruptcy events have been rare and cooperative profitability has rebounded. Although times have been good for cooperatives, history does repeat itself and profitability will become a topic of interest again since cycles are a perpetual facet of agriculture. Risk presents itself in many forms and varies in intensity from period to period making it difficult to mitigate. Credit risk is of particular importance to lenders, managers, and directors. Cooperatives are highly leveraged as a result of limited access to public equity markets and the need to return allocated equity to members; their tendency to narrowly focus on a specific type of commodity, region, or level of the marketing channel contributes to their relatively high business risk (Manfredo & Richards, 2016). Conceptualizing the expected credit risk behavior of cooperatives over time and responses to exogenous favorable and adverse factors offers insight to those interested in cooperatives.

The objective of this thesis is to assess the historical evolution of cooperative credit risk. This will be done by studying the credit rating migration behavior of cooperatives using Markov chains. This research uses proprietary cooperative financial statement data provided by CoBank of 155 cooperatives spanning from 1996 to 2014. The sample data is restricted from 1996 to 2013, and 2014 observations are held and used for out-of-sample forecast evaluation. We use the Credit Metrics component of Moody's Global Agricultural Cooperatives Industry Rating Methodology to assign annual credit ratings. The Credit Metrics component is used to assess a cooperative's financial risk. We then estimate unconditional transition probabilities from the entire sample and vary the time horizon to assess credit migration behavior. Sub-samples conditioned on the type of cooperative, the state of the economy, and the performance of the agricultural sector are created and models estimated to compare differences in migration behavior. Rating drift and rating activity is calculated to assess the trends in credit quality across the sample in addition to rating magnitude. Coefficients of variation and standard errors of the estimates are calculated to measure precision and reliability and the L^2 Norm is used to detect regime change. The estimated transition probabilities are initially assumed to be time-dependent and time-homogenous. However, the literature has found evidence of non-Markovian behavior and the violation of time-homogeneity. Consequently, the impact of these 'time' assumptions on all samples are tested using the Pearson χ^2 and the Likelihood Ratio tests.

The average cooperative in the 1996 to 2013 sample has a prime rating of Baa. Of the 2,790 cooperative years, 75.9% are rated prime, and 24.1% are not rated prime. When the letter grade is considered, only 117 (4.19%) are rated Aaa, the highest possible rating, and 61 (2.19%) are rated Caa, the lowest possible rating. Based on credit migration behavior over the sample, cooperatives are more likely to experience a change in credit rating in the next period than remain unchanged. When the direction of the rating change is considered, the total frequency of upgrades was higher than downgrades. However, when annual observations are considered, there are more instances of downgrades exceeding upgrades from 1996 to 2013. On average, 10.2% of cooperatives change from prime to not prime in credit quality and 10.9% change from not prime to prime. There are many instances whereby downgrades and upgrades span across multiple rating classes. This occurs because cooperatives are small and not diversified enough to withstand adverse challenges to their operations. The rating history impacts the direction of the subsequent rating change. Cooperatives that were previously unchanged in the prior period are more likely to retain their rating in the next period. While those previously upgraded are more likely to be downgraded. And, those previously downgraded are more likely to be upgraded. We find that the rating process does not follow a first-order Markov chain.

1.2 Thesis Objectives

The main objective of this study is to assess the credit rating migration behavior of the risk of agricultural cooperatives. Using Moody's "Credit Metrics" Ratings, this study attempts to answer the following questions:

- How has the credit quality of cooperatives evolved from 1996 to 2013?
- Given an initial rating, are cooperatives more likely to be upgraded or downgraded?
- Is rating stability dependent on credit quality?
- Are future ratings dependent on rating history?
- Is the credit rating migration process a First-order Markov chain?

1.3 Thesis Outline

This thesis is comprised of six chapters. Chapter 2 reviews the literature concerning the credit migration approach, characteristics of migration matrices, challenges to the Markov property and time-homogeneity assumptions, and their respective statistical test procedures.

Chapter 3 outlines the methodology of assigning credit ratings, assessing migration behavior, and the tests used. Chapter 4 describes the data used in this study and provides summary statistics. Chapter 5 states the results of the analysis. Chapter 6 provides conclusions and implications for lenders, and cooperative managers and directors.

Chapter 2 - Literature Review

2.1 The Role and Importance of Credit Ratings

Information asymmetry and adverse selection are age-old problems in debt markets. Without addressing these issues, investors experience high search costs in identifying debt instruments that match their risk profile. Credit ratings are simply assessments of the obligor's repayment ability and consist of subjective and objective components, providing investors with a comprehensive evaluation of an obligor and/or obligation. The United States Securities and Exchange Commission (SEC) established the Nationally Recognized Statistical Rating Organizations (NRSRO) in 1975. Members of this body are registered with the SEC and consequently recognized as having authority on credit quality assessments. Notable members of the NRSRO are "The Big Three", Moody's Investors Service, Standard & Poor's Global Ratings (S&P), and Fitch Ratings. Rating agencies rate the entity—corporations and countries—in addition to the debt instruments they issue. Although their rating scales differ, rating classes are comparable across rating agencies.

2.2 Components of Credit Ratings

Ratings assigned by agencies such as Moody's or Standard & Poor's are a complex judgmental process (Nickell, Perraudin, & Varotto, 2000). A number of resources are collected pertaining to an obligor or obligation. Multiple aspects are considered to provide an overall assessment of repayment ability. Credit ratings consist of objective and subjective components since "fundamental credit analysis incorporates an evaluation of franchise value, financial statement analysis, and management quality" (J. Fons, Cantor, & Mahoney, 2002). Although they are useful in credit risk analysis for investors, they are not intended to capture a specific likelihood of default over a specific time horizon (Wang, Ding, Pan, & Malone, 2017).

Time is an important consideration in evaluating credit quality and the methodology used results in significantly different conclusions. Assessments can either be based on through-the-cycle (TTC) or point-in-time (PIT) methods. PIT parameters consider all relevant, current-state conditions affecting an obligor making it short-term in scope. PIT measures have the characteristics of being timely in reflecting market conditions but are unstable and procyclical (Wang et al., 2017). TTC values are concerned with the long-term to such an extent that the estimated parameters are independent of cyclical effects such as the business cycle or interest rates. Moreover, credit ratings published by agencies aim to reflect perceived permanent (long-term) components of changes in credit quality (Altman & Rijken, 2004). According to Cantor and Mann (2003), the objective of Moody's is to provide "accurate relative (i.e., ordinal) ranking of credit risk at each point in time, without reference to an explicit time horizon".

Observations on the challenges and impact of objective and subjective components are discussed in the literature. Featherstone, Wilson, Kastens, and Jones (2007) primarily studied the challenges lenders face when evaluating the creditworthiness of farm borrowers. The borrower's character, financial record keeping, productive standing, Fair Isaac credit bureau score, and credit risk were considered. Characteristics of the loan officer and the financial institution were also considered. They found the non-financial factors, character and the Fair Isaac credit bureau score, had a significant impact on the proportion of loans approved. In addition, they found the experience of the loan officer and the time they spent on agricultural loans had a significant impact on the proportion of loans approved in Kansas and Indiana.

Gloy et al. (2005) found that subjective components such as a borrower's character, commitment to repay, management capacity, and future business prospects have a stabilizing effect on credit risk ratings since factors such as character and management are unlikely to experience sudden or frequent changes, however, when perceived, substantial changes likely ensue. Unsurprisingly, the authors found that ratings based solely on current and historical records had a higher likelihood of being unstable. Interestingly, stability matters in the debt market.

Fons et al. (2002) found that investors prefer ratings stability and reject the notion of ratings that are more frequently updated. Stability is desired on account of investors wanting to minimize the costliness of portfolio rebalancing (Altman & Rijken, 2004). Huang, Levy, Pospisil, Hong, and Srivastava (2016) acknowledge that even though PIT parameters are more reflective of the current state of the economy, risk measures such as economic capital and unexpected loss becomes more volatile as a result of frequent updates. Clearly, those that benefit from rating stability are bond investors. The same cannot be said for all the issuers the rating agencies evaluate.

Although it may be true that subjective components provide stability, issuers may seem to be at odds with the slowness of updating ratings, an obvious consequence of stability. Survey results in a report by the Association for Financial Professionals (2002) indicated that a third of issuers held the view that assigned ratings were inaccurate, noting that 40% believed agencies were not timely in updating ratings in response to changes in financial quality, and the majority believed when compared to upgrades, downgrades occurred at a faster pace. The timeliness of credit changes is impactful to issuers since borrowing costs are a function of their rating. The longer an issuer stays in a lower credit quality class, the longer they are subject to higher borrowing costs.

In addition to their lack of timeliness, rating agencies have received several complaints over the years most notably regarding their rating methodologies. Their methodologies are of interest to the public and in order to be more transparent are regularly published. Unfortunately, the construction of subjective components inherent in the published ratings are difficult to discern yet alone model, even with an articulated rating methodology. According to Nickell et al. (2000), one cannot be sure if the resulting probability distribution modeled is similar to those a rating agency might produce since the credit risk categories used are explicitly non-quantitative and are not directly linked to likelihoods of default. This is demonstrated in their unusual results of their model for Japan and the United Kingdom as they did not contain probabilities of downgrades into non-investment grades or default. Therefore, credit rating methodologies should not be regarded as precise since they rely on the judgement and experience of the agencies (Crouhy, Galai, & Mark, 2001).

2.3 The Credit Migration Approach

The value of using the credit migration approach is that it results in a comprehensive perspective on credit risk and loan losses than relying solely on the measurement of historic default rates (Barry, Escalante, & Ellinger, 2002). Credit migration approaches can vary in complexity, but their applications are broad. Early finance applications of credit migration conducted by Cyert, R., & Thompson, G. (1968) illustrate the theory's usefulness whereby they developed a model that allowed a firm to better discern credit risk and improve controls in the issuance of credit cards. With the passage of time, Markov chain applications were used to assess portfolio risk (Altman & Kao, 1992a; Belkin, Suchower, & Jr, 1998; L. V. Carty & Fons, 1993; Duffee, 1998; J. S. Fons, 1994; Helwege & Turner, 1999; Lucas & Lonski, 1992) and valuing credit derivatives and instruments (Bielecki & Rutkowski, 2000; Jarrow, Lando, & Turnbull, 1997; Kijima & Komoribayashi, 1998; Lando, 1998, 2000). Unfortunately, the proprietary nature of loan data, small portfolios, and the tendency for lenders to change their rating methodologies within the agricultural sector have resulted in the limited number of credit migration studies (Gloy et al., 2005).

The common, underlying assumptions imposed to derive credit migration matrices in the literature are that the stochastic process is a First-order Markovian and time-homogenous. A Markov chain that is first-order means that the current state of the system is only dependent on the last period's state. A first-order Markov chain that is time-homogenous has a probability distribution that does not change over time. This property is also known as stationarity.

2.4 Estimating Credit Migration Matrices

Anderson and Goodman (1957) found that transition probabilities calculated from the entire sample to be Maximum Likelihood Estimators. They found them to be consistent but biased. However, they found the bias tended to zero as the sample size increased.

Estimated probabilities can be compared to observed probabilities from the sample data to determine the accuracy of the prediction. Altman and Kao (1991) measured the predictive ability of their models as deviations from the estimated values. They found that their models' predictive ability worsened over time, that is, they are best at estimating distributions within shorter periods. They state that it is unacceptable to make predictions from the sample data as it creates a self-fulfilling prophecy and suggest the results be back tested or predictions be compared with out-of-sample observations.

Bangia et al. (2002) found diagonal elements to be the most accurate and observed an increase in variation the further away one moved from the diagonal by computing coefficients of variation to represent the level of uncertainty. Nickell et al. (2000) calculated the standard errors of each probability to show the precision of the estimates. According to Jones (2005), datasets provided by credit rating agencies suffer from survivor bias if failed assets are excluded resulting in inaccurate estimates. However, he states that a “survivors” transition matrix can be estimated on a consistent basis if it is not feasible to observe defaults.

At times an estimated transition matrix will not yield similar results to those found in literature. “The nature and extent of the problems encountered will be a function of the particular rating system, the number of grades considered, and the amount of historical data available” (J.P.Morgan, 1997). Prominent rating agencies use modifiers, numeric (1, 2, & 3) in the case of Moody’s Investors Service while S&P uses a plus (+) or minus (-), to add granularity and show the credit quality of an issuer within a rating class. Unfortunately, such granularity does not lend itself well to estimating transition matrices. The number of observations within low credit rating categories with modifiers is not sufficient; the small sample size has a negative impact on statistical inference, and therefore, the industry standard is to publish transition matrices without rating modifiers (Bangia et al., 2002).

Another modeling complication is the pace of change in credit quality when dealing with continuous-time rating observations provided by rating agencies. According to Jones (2005), credit quality may respond too slowly to changes in the economy making the first-order Markov chain too restrictive. He suggests using a longer time horizon or higher-order Markov chain, but the limitation is that it requires a rich dataset. On the other hand, credit quality may respond quickly to changes in the economy, but observations aren’t made at the same pace (Jones, 2005). A notable period was during the Great Recession in which the “Big Three” failed to provide sufficient credit quality updates on securitized debt instruments. In the same vein, Nationally Recognized Statistical Rating Organizations failed to predict the defaults of Enron and Worldcom. Moreover, the literature indicates that most bond or stock price changes occur prior to the actual rating change announcement (Altman & Kao, 1991).

2.5 Migration Rate Behavior

A credit migration matrix has a few characteristics worth mentioning. An expectation is that there is a rank order of transition probabilities as follows:

1. Higher quality credit ratings are not correlated with a higher likelihood of default;
2. The greater the difference between two rating classes i.e. migration distance, the lower the likelihood of transition;
3. The smaller the difference between two rating classes (notches), the higher the likelihood of transition (J.P.Morgan, 1997).

The rank order gives rise to the term monotonicity that describes the declining transition probability the further two states are from each other. Violations to the rule may occur in the event of default however, since default is an absorbing state and probabilities accumulate over time, an exception can be made (Berd, 2005). Bangia et al. (2002) found additional violations to monocity and attributed the results to "intra-interval rating activity omissions inherent in longer transition horizons" and "noise in the underlying data". Nickell et al. (2000) observed that the distribution of probabilities in their study varied with the business cycle, along with the industry the obligor belonged to, and the elapsed time since debt issuance.

There is a "high probability load on the diagonal" indicating that borrowers have a high likelihood of maintaining their current rating (Bangia et al., 2002). Therefore, it is expected to observe the highest probabilities of the matrix concentrated in the diagonal followed by neighboring probabilities. These diagonal elements are conventionally known as retention rates. Volatility is the likelihood that an entity fails to retain their rating in the next period whereas stability is the opposite in definition. Using a Moody's dataset spanning from 1970-1997 consisting of 6,534 obligors, Nickell et al. (2000) found a 90% retention rate for obligors rated

Aaa and Aa, 85.7% for Ba rated issuers, 83.0% for B, and 66.6% for Caa. They concluded that volatility increased as credit quality declined. According to Jorion, Shi and Zhang (2005), notable differences in the stability of transition probabilities of investment and speculative rated issuers were found to have been attributed to "differences in the value relevance of accounting data and in earnings management".

Barry, Escalante, and Ellinger (2002) applied the migration approach to farm-level data from the Illinois Farm Business Farm Management Association (FBFM) by observing the historic movement of farmers' credit scores derived from a five-class model developed by Splett, Barry, Dixon, & Ellinger (1994) and other performance measures under different time-average approaches. Consistent with empirical results, "the frequencies are highest for remaining in the same class, the rates decline for movements to more distant classes, and the incidence of downgrading tends to exceed the occurrence of upgrading" (Barry et al., 2002).

Escalante, Barry, Park, and Demir (2004) utilized a probit regression to determine the factors that significantly impact the probability of farm credit migration rates. Transition probabilities were obtained from the five-class model developed by Splett et al. (1994) and a ten-class rating model recommended under the Basel Accord. Class 1 represented the lowest risk borrowers in the five-class model, subsequent classes represented increasing credit risk, and Class 5 represented default. Similar to the results of Barry et al. (2002), Escalante et al. (2004) found retention rates to be highest for Class 1 borrowers, middle lower credit risk classes diminished, and borrowers that belonged to Class 5 slightly increased. Retention rates under the ten-class model were found to be significantly lower than those in the five-class model. Carty (1997) states that finer gradation in the rating scale results in higher volatility since small changes in credit quality are more likely be captured. As observed in the five-class model of

Escalante et al. (2004), Class 1 of the ten-class model exhibited the highest retention rates relative to other classes. However, unlike the findings of Nickell et al. (2000) and Carty (1997), retention rates did not decrease monotonically with decreasing credit quality in both the five-class and ten-class models.

Altman and Kao (1992b) studied the behavior of bonds issued in the 1970–1988 period. They were interested in observing the significance of the initial rating and the resulting probability distribution. They found bonds initially rated A and higher were more likely to be downgraded than upgraded. Within 10 years of issuance, 40–80% of initially rated BB bonds and higher were expected to experience at least one transition, and bonds rated A were more stable than AAA. The lowest quality rated in the dataset were BB-rated and unsurprisingly were found to be the most unstable. All bonds with an initial credit classes belonging to the investment grade subset had a higher likelihood of downgrade except for those rated BBB and no pattern was observed for non-investment grade bonds.

Altman and Kao (1991) found that retention rates declined as the investment horizon increased implying increased volatility. Carty and Fons (1993) found Baa rated issuers were more likely to be upgraded than downgraded for time horizons greater than one year. Higher rated issuers were more stable than riskier issuers and exhibited a lower probability of default (L. V. Carty, 1997; Figlewski, Frydman, & Liang, 2012). However, Carty and Fons (1993) state that the highest rated issuers' likelihood of downgrade eventually increases with the time horizon because they cannot be upgraded any further. In a study by Blume, Lim, and MacKinlay (1998), average credit ratings for investment grade issuers from 1978 to 1995 decreased but these findings were attributed to tightening credit standards. Carty and Fons (1993) found that net downgrades exceeded net upgrades for Aa and A rated classes for a one-year, two-year, five-year and 10-year horizons. They also found issuers rated Baa to have an approximately equal likelihood of an upgraded or downgrade, but issuers rated B were more likely to be upgraded than Ba. Interestingly, Carty and Fons (1993) observed Caa-rated issuers were more likely to default on account of being “too weak to make the uphill climb”, a significant contrast to the results of Lucas and Lonski (1992) who found the proximity of the Ca and C rating to the default state resulted in more stable probabilities.

2.6 Challenges to the Markov Property Assumption

There is ample evidence in the literature of the Markov property and time-homogeneity being violated. Nickell et al. (2000) found probability distributions to be dependent on the stage of the business cycle and industry sector. One may control for the stages of the business cycle and still observe non-Markovian behavior. Frydman and Schuermann (2008) found that despite two firms having identical current ratings, they can have markedly different probability distributions and non-Markovian behavior still persists after controlling for the business cycle or industry sector. Additional sources to non-Markovian behavior have been identified in the literature. This study will focus on path dependence, industry sector, and fallen angel events.

2.6.1 Path Dependence

According to Carty and Fons (1993) “prior rating changes carry predictive power for the direction of future rating changes”. This is known as rating momentum or path dependence. It is the observation that last period’s rating has some bearing on the direction of transition in the following period.

Before discussing path dependence further, the term rating drift and its variation in definition in the literature are discussed. Rating drift is defined as how ratings change over time (Altman & Kao, 1991, 1992a, 1992b; Altman & Rijken, 2004) where migration rates are compared under differing time horizons. Rating drift overestimates “the performance of individual bonds and the whole portfolio under some assumed yield curve changes.” (Altman & Kao, 1991). This definition is different to that of Carty (1997) who calculates “annual rating drift” by summing the total number of upgrades—weighted by the number of ratings changed per upgrade—per year less total number of downgrades— weighted by the number of ratings changed per upgrade—per year, divided by the total number of non-defaulted obligors at risk of a rating change during the period. According to Carty (1997), changes in rating drift indicate a change in the credit quality of a portfolio as a percentage of one rating per issuer. If the calculated rating drift is positive, then the portfolio improved in quality while a negative rating drift is a deterioration in quality. Lando and Skødeberg (2002) define rating drift as the current rating’s dependence on the previous rating. In their study, rating drift is equivalent to rating momentum.

Rating momentum was observed and discussed in Carty and Fons (1993). However, Lando and Skødeberg (2002) were critical of how they addressed non-Markovian behavior. Carty and Fons (1993) tested two hypotheses; the first being that within one year there is no upward rating momentum and the second is that there is no downward rating momentum. Rating momentum is conditioned on the current period having the same direction as the prior. They failed to reject the no upward momentum hypothesis at the 5% level of confidence except for the B rated category and rejected the no downward momentum at the 5% level of confidence at all rating categories. That is, “a downgraded issuer is more prone to a subsequent downgrade within one year than an upgrade” (L. V. Carty & Fons, 1993).

According to Lando and Skødeberg (2002), what Carty and Fons (1993) failed to account for is that the nature of a Markov chain suggests that probabilities across rating classes could be higher for downgrades than upgrades and that the distinction that ought to be made is the direction taken to arrive at the current state not the departure from the current. They believe that rating momentum observed in their study was likely a function of the rating grade concentration of firms in the sample since observations concentrated in investment grade ratings would have different results than a sample with a concentration of firms that were non-investment grade. They suggest testing the rating behavior of obligors with specific ratings to those of obligors that arrived at their current credit rating through an upgrade or downgrade.

In a study by Figlewski et al. (2012), path dependence was observed as previously downgraded firms were found to have a higher likelihood to experience a further downgrade and to default than an equally-rated firm that had not experienced downgrade in the prior period. Similarly, Altman and Kao (1992b) found a pattern of a downgrade to be followed by a second downgrade in the two sub-periods of the data sample but no presence of path dependence when an upgrade initially occurred.

Bangia et al. (2002) evaluated three momentum matrices—upward, downward and maintain—against the unconditional matrix and found downgrade probabilities of the downward momentum matrix to be larger than their corresponding elements in the unconditional matrix while downgrade probabilities of the upward momentum matrix were smaller. They also found the upgrade probabilities of the upward momentum matrix for non-investment grade credit classes to be higher than their corresponding elements in the unconditional matrix, while investment grade credit classes were lower.

2.6.2 Industry Sector

In their study, Nickell et al. (2000) constructed a matrix conditioned on industry—Banking versus Industrial—and found banks' probabilities to be less stable than those of industrials since the retention rate for banks were lower for all rating classes. They calculated t-statistics at a 5% level and compared their conditional matrix to the unconditional and found approximately half the estimates for banks to be statistically significant and in addition, found that estimates for industrials were generally similar. Similarly, Altman and Kao (1991) found that bonds belonging to the industrial sector were more stable than non-industrials.

2.6.3 Fallen Angels

Fallen angels are issuers that are downgraded from investment grade to speculative (non-investment) grade. Fallen angels have markedly different probability distributions to their equally-rated peers (Figlewski et al., 2012; Mann, Hamilton, Varma, & Cantor, 2003). Emery and Gates (2014) found 42% of fallen angel events were attributed to company specific factors and 30% to industry stress. Furthermore, they found the median downgrade due to leveraged acquisitions fell five rating classes compared to the one to two class fall for all other reasons.

According to Mann et al. (2003) relative to equally-rated, non-investment grade debt, fallen angels have longer maturities, larger debt size, smaller coupons, and fewer covenants. In the first two years after being downgraded, fallen angels were found to have a higher likelihood of default and a lower likelihood to be upgraded to investment grade relative to equally-rated non-investment grade issuers but their investment profile improved better than non-investment grade issuers as time progressed (Mann et al., 2003).

The initial rating assigned to a fallen angel has a bearing on the transition probability; the lower the initial assigned rating the more likely the firm will default, and the higher the initial assigned rating, the higher the likelihood of returning to an investment grade rating (Emery & Gates, 2014; Mann et al., 2003). Of the 477 fallen angels studied by Emery and Gates (2014) spanning a period from 1999–2003, 39% remained in the non-investment grade rating, 28%

upgraded to investment grade, 15% defaulted, and 18% of the firms had their ratings withdrawn. Furthermore, they observed a spike in frequency of fallen angel events during the 2001–2002 period but surprising, there was no similar run-up during the 2008 Financial Crisis, but they believe it was likely explained by the fact that the firms were non-financial entities, in addition to increased risk-taking and liquidity as a result of Quantitative Easing (QE) (Emery & Gates, 2014).

2.7 Challenges to the Time-Homogeneity Assumption

In addition to the Markov property being violated, there are examples in the literature of time-heterogeneity. The violation of time-homogeneity can be attributed to the sampling process. "Markov chains are not usually stationary, in the sense that the joint distribution of N successive observations may be different depending on where they are taken"(Kiefer & Larson, 2007). The transition estimates may be significantly different depending on the period length of the sample (Altman & Kao, 1991). This cannot easily be addressed by taking a sample that spans a longer time period. This is because longer time periods have a higher risk of regime change (Bickenbach & Bode, 2003). Longer time periods are more likely to capture numerous events such as industry specific and systemic incidents, natural disasters, governmental policy changes, and the business cycle as demonstrated by Nickell et al. (2000). These events would undoubtedly influence credit migration behavior. Controlling for them would be difficult let alone identifying them individually. The consequence of not identifying time-inhomogeneity in a sample is that the estimates will not be a true prediction of the future distribution of ratings (Altman & Kao, 1992b).

2.7.1 The Business Cycle

It is important to examine a period that covers various economic conditions since the variance of default rates are a function of economic conditions; recessions beget higher frequencies of defaults while expansions decrease them (Jorion et al., 2005). Moreover, the failure to do so yields probabilities that are sensitive to the sample period chosen and are not representative of a given transition (Jones, 2005). Helwege and Kleiman (1997) found that a downturn economy leads to a higher frequency of defaults. A higher prevalence of defaults can be explained by the idea that firms operating in a recessionary environment may find their ability to generate profits impaired which impacts their ability to pay its bondholders (Helwege & Kleiman, 1997).

Nickell et al. (2000) categorized their sample years into economic activity levels “peak”, “normal times”, and “trough” for G7 and non-G7 countries that corresponded to the sample’s recorded real GDP growth rate—upper, middle, or lower third. They found investment grade bonds were significantly more stable in “peak” periods and stability deteriorated in “troughs”. In addition, their results indicate the likely effect of the business cycle on investment grade issuers was a decrease in stability rather than an increased likelihood of downgrade and that default probabilities “depend strongly on the stage of the business cycle”.

Bangia et al. (2002) estimated conditional and unconditional ratings transition matrices whereby conditional matrices were conditioned on the stage of the business cycle and unconditional matrices were averaged across all stages of the cycle. Conditional transition matrices indicated significant differences in the loss distribution of credit portfolios. Their resulting downgrade transition probabilities were higher but more stable during recessionary periods and lower for upgrades.

2.8 Testing the Assumptions

The assumptions of Markovian behavior and time-homogeneity are important "because loans prior to maturity can be substituted by new loans with the same rating and the rating quality can be expected to develop in a similar manner" (Weissbach, Tschiersch, & Lawrenz, 2009). This illuminates the importance of testing and confirming the assumptions. An incorrect estimated distribution results in incorrect predictions about the future. In as much as these assumptions make modeling credit risk simple, and hence their popularity, they are restrictive, unrealistic, and likely to be violated (Kiefer & Larson, 2007).

The reliability of estimated transition probabilities requires the data-generating process to be Markovian and the estimates be based on a sufficiently large number of observations (Bickenbach & Bode, 2003). They state that a violation of the Markov property and time-homogeneity results in the inability to derive an accurate stationary distribution and secondly, insufficient observations result in inaccurate probabilities reflected by high standard errors. Tan and Yılmaz (2002) state that even if the process is confirmed to be first-order dependent it cannot be assumed to be time-homogenous. Moreover, they state that if the process is time-inhomogeneous then the Markov chain has no predictive power. Therefore, testing both assumptions is required to conclude that the rating process is a first-order Markov chain.

Time-inhomogeneity can be tested by calculating cell-by-cell distances, L^1 Norm and L^2 Norm (Euclidean Distance), comparing annual matrices to the entire sample's average transition matrix (Gunnvald, 2014; Jafry & Schuermann, 2004; Trück & Rachev, 2011). Unfortunately, the two metrics "only provide a relative comparison between two matrices" because one is unable to determine which of the two is larger nor interpret the magnitude of the resulting Euclidian distance (Jafry & Schuermann, 2004).

Anderson and Goodman (1957) were some of the early contributors of statistical tests for testing the assumptions of a Markov chain. They applied the Likelihood Ratio and Pearson χ^2 tests on the following hypotheses:

(a) the estimates of the first-order chain were time-homogeneous;

(b) if they were time-homogenous, then were they specified numbers;

(c) and whether the stochastic process is a u-th order Markov chain against the alternative hypothesis that it is an r-th but not u-th order (Anderson & Goodman, 1957).

Following the principles outlined by Anderson and Goodman (1957), Bickenbach and Bode (2003) tested time-homogeneity by dividing their entire sample into mutually exclusive and exhaustive sub-periods and compared the estimates of the sub-periods to those of the entire sample. They used the Likelihood Ratio and Pearson χ^2 tests to evaluate the hypothesis that the probabilities from the sub-periods were equal to those in the entire sample.

Tan and Yılmaz (2002) tested two sequential orders at a time to evaluate the order of the Markov chain. The hypothesis was that the estimates were equal. They began by comparing the zero-order Markov chain to the first-order Markov chain. If that test was rejected, then the conclusion would be that the process was not a zero-order Markov chain. They then compare the first-order Markov chain to the second-order Markov chain. If the null hypothesis cannot be rejected, then one can conclude that the stochastic process was a first-order Markov chain.

2.9 Summary of the Literature

The literature suggests that the subjective component of credit ratings have a stabilizing effect on ratings and this characteristic is demanded by investors. Retention rates were found to most likely have the highest probability in a migration matrix and were observed to decrease with time. Transition probabilities were also found to vary with the business cycle and with the industry the obligor belonged to. Non-Markovian behavior such as path dependence, and fallen angel events, including non-stationarity have been identified in studies. The literature provides statistical methods to test the Markov property and stationarity. It also provides estimates such as the standard error and coefficient of variation for measuring the accuracy of the transition probabilities. Many of the concepts summarized in the literature review are yet to be comprehensively considered and applied to agricultural cooperatives. This study contributes to the literature by assessing the credit rating migration behavior of agricultural cooperatives.

Chapter 3 - Methods

3.1 Moody's Global Agricultural Cooperatives Industry Rating Methodology

Founded in 1909, Moody's is a respected and authoritative institution in the credit rating industry. This study follows Moody's Rating Methodology: Global Agricultural Cooperatives Industry (2010) to assign annual credit ratings for each cooperative in the sample. Credit quality assessments published by rating agencies have subjective and objective components. Although Moody's methodology offers detailed illustrations of the evaluation methods and considerations made when rating a cooperative, it is unlikely that this study could produce an assessment identical to that of one produced by Moody's. The inability to follow the complete Moody's methodology is because the subjective components of the rating methodology cannot be created. For this reason, this study only makes use of the objective component in the rating methodology titled Credit Metrics.

3.1.1 Moody's Overall Rating Process

Moody's (2010) credit assessments are based on four broad rating factors:

1. Scale and diversification
2. Franchise strength and growth potential
3. Financial flexibility
4. Financial strategy and Credit Metrics

Table 3.1 shows Moody's Rating Grid. It consists of the rating factors, the sub-factors, and their respective weights that are used in determining the overall rating a cooperative receives.

Table 3.1 Rating Grid: Factors, Sub-factors, and Weights

RATING FACTORS	SUB-FACTORS	WEIGHTING	CUMULATIVE SUB-FACTOR WEIGHTING
1. Scale and Diversification	a) Total Sales (USD Billion)	5.00%	25.00%
	b) Geographic Diversification – Sales Sales Concentration to a Single Market Region **And** Sales to Developed Market Regions	5.00%	
	c) Geographic Diversification – Raw Materials Supply Concentration from a Single Producing Region	5.00%	
	d) Segmental Diversification	10.00%	
2. Franchise Strength and Growth Potential	a) Market Share	5.00%	20.00%
	b) Organic Volume Growth	5.00%	
	c) Qualitative Assessment of Portfolio	10.00%	
3. Financial Flexibility	a) Willingness and Ability to Reduce Member Payments; Relative Size of Member Payments	10.00%	10.00%
4. Financial Strategy and Credit Metrics	a) Financial Strategy	5.00%	45.00%
	b) Debt / Coop EBITDA	10.00%	
	c) Coop RCF / Net Debt	10.00%	
	d) Coop EBITA / Interest Expense	10.00%	
	e) (Coop RCF-Capex) / Debt	10.00%	
Total		**100.00%**	**100.00%**

Note. Reprinted from "Rating Methodology: Global Agricultural Cooperatives Industry" by Moody's Investors Service (Moody's Investors Service, 2010).

Each rating factor consists of sub-factors. Credit Metrics is the only objective rating factor and it consists of four sub-factors. They are:

1. Debt / Cooperative Earnings Before Interest, Taxes, Depreciation and Amortization (EBITDA)
2. Cooperative Retained Cash Flow (RCF) / Net Debt
3. Cooperative Earnings Before Interest and Taxes and Amortization (EBITA) / Interest Expense
4. Cooperative RCF less Capital Expenditures / Debt

These credit metrics are a gauge of financial quality and are believed to be the most important in assessing financial credit risk (Moody's Investors Service, 2010).

Moody's defines the four credit metrics as:

Debt / Cooperative Earnings Before Interest, Taxes, Depreciation and Amortization (EBITDA) reflects operating cash flow available for debt service before interest. This ratio remains a key ratio utilized by speculative-grade investors, but has limitations for credit analysis because it does not reflect capital spending or working capital requirements. In addition, the EBITDA measure does not take into account exceptional items below the EBITDA line that could impact cash flow.

Cooperative Retained Cash Flow (RCF) / Net Debt: Retained Cash Flow examines operating cash flow before working capital changes but after all cash payments to and contributions from members. This metric reflects the cash generation ability of the business relative to debt burden, regardless of how management chooses to distribute cash payments to cooperative members. Thus, RCF reflects all member cash distributions and receipts including produce payments (COGS), net earnings paid in cash (dividends), equity retains (share issuances) and retirements of equity (share buybacks).

Cooperative Earnings Before Interest and Taxes and Amortization (EBITA) / Interest Expense is a debt service measure which has a major advantage: its takes seasonality into account. This is particularly important in assessing companies that tend to reduce debt solely at year-end for balance sheet presentation purposes, or that end their financial reporting year when debt is at its annual low-point. The major drawback of this measure is that interest expense may vary according to the date of debt issuance or the mix of fixed or floating rate debt instruments.

Cooperative RCF less Capital Expenditures / Debt assesses sustainable debt repayment capacity prior to working capital movements. Paradoxically, speculative-grade issuers may have relatively high free cash flow metrics compared to their investment-grade counterparts as they tend have weaker franchises with mandatory debt reduction schedules and less ability to withstand business challenges. (Moody's Investors Service, 2010, p. 17).

3.1.2 Calculating the Credit Metrics

Moody's makes two important accounting adjustments when calculating credit metrics. The adjustments are necessary for the purposes of consistency and comparison. First, Moody's estimates are based on a cooperative's ability and willingness to lower patronage and adds it back to gross margin. The add-back value ranges from 0% to 7%. According to Moody's (2010) the add-back value does not exceed 7% since reducing patronage by more than 7% disrupts membership stability. However, the process in determining the value is subjective therefore it is assumed that the add-back value for all cooperatives is 5% for the purposes of this study.

The second adjustment is on the cost of goods sold (COGS). Moody's treats COGS as patronage income to better reflect how cooperatives distribute residual claims to members. Motivation for the adjustment can be observed when accounting for member payments since some cooperatives reflect member payments in the COGS line while others place them in the statement of cash flows (Moody's Investors Service, 2010). Table 3.2 illustrates a comparison of two cooperatives that account for member payments differently; one does not include a portion of member payments explicitly as COGS while the other does.

Table 3.2 The Effect of Member Payments in the form of Cost of Goods Sold

($ MILLIONS)	NO COGS COOP NO CORN COST IN COGS	YES COGS COOP INCLUDES CORN COST IN COGS
Sales	100	100
Cost of goods sold - processing costs	-20	-20
Cost of goods sold - corn	-	-60
Gross profit	80	20
SG&A	-10	-10
Operating profit	70	10
Traditional operating margin	70%	10%
Interest	-4	-4
Taxes	-1	-1
Net income	65	5
Cash patronage payments to farmers	-63	-3
Earnings retained in COOP	2	2

Note. Reprinted from "Rating Methodology: Global Agricultural Cooperatives Industry" by Moody's Investors Service (Moody's Investors Service, 2010).

Although margins and line item balances are different between the two cooperatives, they distribute the same total amount of member payments and are financially equal. The no COGS cooperative lists all payments made to members in the Cash patronage payments to farmers line while the yes COGS cooperative splits member payments between the Cost of goods sold - corn and Cash patronage payments to farmers lines.

Moody's procedure for calculating the respective components of the four credit metrics are shown in Table 3.3. This research calculates Total Member payments for produce as COGS for Commodities + COGS for Processed Goods + COGS for Supplies. Funds from Operations before Add-back will be calculated as Net Income + Depreciation + Amortization – Net Gain on Asset Sales.

Table 3.3 Financial Statement Steps for Calculating Credit Metrics

Net Sales
COGS
TOTAL MEMBER PAYMENTS
Total member payments for produce
+ Gross cash payments to retire members equity
+ Net savings paid in cash
- Current year cash equity retains
=Total member payments
% of member payments Add-back
Add-back Amount
CASH FLOW ADJUSTMENTS
Funds from Operations before Add-back
+ Add-back Amount
= COOP Funds from Operations (FFO)
- Non-member dividends
- Gross cash payments to retire members equity
- Net savings paid in cash
+ Current year cash equity retains
= COOP Retained Cash Flow (RCF)
INCOME STATEMENT ADJUSTMENTS
Member payments included in COGS?
Earnings Before Interest Taxes and Amortization
- Member produce payments NOT included in COGS
+ Add-back Amount
COOP Earnings Before Interest Taxes and Amortization (EBITA)
+ Depreciation
= COOP Earnings Before Interest, Taxes, Depreciation and Amortization (EBITDA)
OTHER FINANCIAL DATA
Total Debt
- Cash
= Net Debt
Interest Expense
Capital Expenditures

Note. Reprinted from “Rating Methodology: Global Agricultural Cooperatives Industry” by Moody’s Investors Service (Moody’s Investors Service, 2010).

3.1.3 Mapping the Credit Metrics Factor to Rating Categories

Once the credit metrics have been calculated the next step is to map them to their respective sub-factor ratings. Each credit metric has a range that corresponds to seven respective sub-factor rating categories (i.e., Aaa, Aa, A, Baa, Ba, B, and Caa) whereby Aaa is the highest rating possible and Caa is the lowest. Investment grade ratings consist of Aaa, Aa, A, and Baa. Non-investment grade ratings consist of Ba, B, and Caa. Once the sub-factor ratings have been determined, the next step is to map them to their respective sub-factor score. Table 3.4 illustrates the numerical ranges of the four credit metrics and what sub-factor rating categories they fall under.

Table 3.4 Mapping Credit Metrics to Sub-Factor Ratings

	Aaa	**Aa**	**A**	**Baa**	**Ba**	**B**	**Caa**
Debt / Coop EBITDA	<1.0x	≥1.0x - 1.5x	≥1.5x - 2.3x	≥2.3x - 3.3x	≥3.3x - 4.5 x	≥4.5x - 6.0x	≥ 6.0x
Coop RCF / Net Debt	≥50%	≥37 - 50%	≥27 - 37%	≥19 - 27%	≥12 - 19%	≥8 - 12%	<8%
Coop EBITA / Interest Expense	≥18.0x	≥13.0 - 18.0x	≥9.0 - 13.0x	≥5.0 - 9.0x	≥2.5 - 5.0x	≥1.5 - 2.5x	<1.5x
(Coop RCF - Capex) / Debt	≥35%	≥27 - 35%	≥17 - 27%	≥10 - 17%	≥6 - 10%	≥3 - 6%	<3%

Note. Reprinted from “Rating Methodology: Global Agricultural Cooperatives Industry” by Moody’s Investors Service (Moody’s Investors Service, 2010).

Table 3.5 illustrates the mapping of sub-factor ratings to their corresponding sub-factor scores. There are 7 categories of sub-factor scores (i.e. 1, 3, 6 , 9, 12, 15, and 18) corresponding to a sub-factor rating. Translating them to their numerical equivalent allows for a weighted score to be determined that can then be mapped to the overall grid-indicated rating.

Table 3.5 Sub-Factor Mapping/Scoring

Measurement Outcome	Strongest<--> Weakest						
Sub-Factor Rating	Aaa	Aa	A	Baa	Ba	B	Caa
Sub-Factor Score	1	3	6	9	12	15	18

Note. Reprinted from “Rating Methodology: Global Agricultural Cooperatives Industry” by Moody’s Investors Service(Moody’s Investors Service, 2010).

3.1.4 Determining the Overall Grid-Indicated Rating

The overall rating process assigns equal weights to the credit metrics in determining the indicated rating. Similarly, this study assigns equal weights to the four credit metrics. The aggregate weighted score is determined by the following formula:

$$\sum_{n=1}^{4} sub\text{-}factor_n score * sub\text{-}factor_n weight.$$

The resulting aggregate weighted score is then mapped to the indicated rating as shown in Table 3.6. Since there are only 19 annual observations for 162 cooperatives, the granularity of the 18 rating categories likely results in their respective frequencies being too low. Therefore, the numerical modifier is dropped, and seven rating categories are used (i.e. Aaa, Aa, A, Baa, Ba, B, Caa). Ratings Aaa1, Aaa2, and Aaa3 are consolidated to Aaa, ratings Aa1, Aa2, Aa3 are consolidated to Aa, and so on. The ratings that this study assigns to cooperatives following the aforementioned rating methodology are Credit Metric Ratings and explicitly describe the credit quality of cooperatives implied by their respective financial positions only.

Table 3.6 Mapping the Indicated Rating to the Alphanumeric Rating

INDICATED RATING	AGGREGATE WEIGHTED FACTOR SCORE RANGE				
Aaa			x	<	1.5
Aa1	1.5	≤	x	<	2.5
Aa2	2.5	≤	x	<	3.5
Aa3	3.5	≤	x	<	4.5
A1	4.5	≤	x	<	5.5
A2	5.5	≤	x	<	6.5
A3	6.5	≤	x	<	7.5
Baa1	7.5	≤	x	<	8.5
Baa2	8.5	≤	x	<	9.5
Baa3	9.5	≤	x	<	10.5
Ba1	10.5	≤	x	<	11.5
Ba2	11.5	≤	x	<	12.5
Ba3	12.5	≤	x	<	13.5
B1	13.5	≤	x	<	14.5
B2	14.5	≤	x	<	15.5
B3	15.5	≤	x	<	16.5
Caa1	16.5	≤	x	<	17.5
Caa2	17.5	≤	x		

Note. Reprinted from "Rating Methodology: Global Agricultural Cooperatives Industry" by Moody's Investors Service (Moody's Investors Service, 2010).

3.2 Markov Chain Theory

The theory and derivation of this section follows Resnick (2013, pp. 60–147).

3.2.1 Stochastic Processes

A stochastic process $\{X_n\}_{n \in \mathbb{N}_0}$ is a collection of random variables indexed by a mathematical set known as the *index set*, *n*, and the random variable takes values in a countable set S known as the *state space* where $S = \{1, 2, \dots, m\}$.

3.2.2 The Markov Property

The *Markov Property* or *First Order Markov Condition* assumes that the future value of the random variable only depends on its current value, thus past values are irrelevant. This property implies that the process is *memoryless*.

3.2.3 The Discrete-Time Markov Chain

A discrete-time Markov Chain is a stochastic process $\{X_n\}_{n\in\mathbb{N}_0}$with a Markov Property that takes on values in a countable state space S if,

$$\mathbb{P}[X_{n+1} = i_{n+1}|X_n = i_n, X_{n-1} = i_{n-1}, \dots, X_1 = i_1, X_0 = i_0] = \mathbb{P}[X_{n+1} = i_{n+1}|X_n = i_n], \quad (1.1)$$

for all $n \in \mathbb{N}_0$, and all $i_0, i_1, \dots, i_n, i_{n+1} \in S$. The process will initiate in one of the states in S. Over an interval of time, the process may move to another state. This single move is known as a *step*. In general, the element in *S* representing the current state is denoted by i and the element representing the future state will be denoted by j. Therefore (3.1) can be rewritten as,

$$\mathbb{P}[X_{n+1} = j|X_n = i]. \quad (3.2)$$

3.2.4 Transition Probabilities and Time-Homogenous Markov Chains

The likelihood of a step from state *i* to state *j* is called the transition probability denoted as p_{ij}. Likewise, the likelihood that the process remains in state *i* is denoted as p_{ii}. When p_{ij} is independent of time *n*, that is,

$$\mathbb{P}[X_{n+1} = j|X_n = i] = p_{ij}, \quad (3.3)$$

then the probabilities are time-homogenous or stationary.

3.2.5 Initial Probability Distribution

There exists a probability distribution when the Markov chain i.e. the system, initiates at time $n = 0$. This distribution is a vector and is known as the *Initial Probability Distribution*. The probability $\mathbb{P}[X_0 = i]$ that the system initiates in state i is denoted as:

$$p_i,$$

whereby

$$p_i \geq 0,$$

for all $i \in S$ and

$$\sum_{i=1}^{m} p_i = 1.$$

The path that the system takes can be simplified to

$$\mathbb{P}[X_0 = i_0, X_1 = i_1, \dots, X_n = i_n] = p_{i_0} p_{(i_0, i_1)} p_{(i_1, i_2)} \dots p_{(i_{n-1}, i_n)}$$

as the product of the initial probability distribution and all the elements in the matrix representing the path taken.

3.2.6 One-Step Transition Matrices

The collection of transition probabilities corresponding to all possible single step transitions between states in S is called the *one-step transition matrix* denoted as,

$$\mathbf{P} = (p_{ij})_{i,j \in S}, \tag{3.4}$$

and represented graphically as,

$$\mathbf{P} = \begin{bmatrix} p_{11} & p_{12} & \cdots & p_{1n} \\ p_{21} & p_{22} & \cdots & p_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ p_{n1} & p_{n2} & \cdots & p_{nn} \end{bmatrix} \tag{3.5}$$

The *m x m* transition matrix **P** must satisfy the probability law

$$p_{ij} \geq 0,$$

for $\forall_{i,j} \in S$ and

$$\sum_{j=1}^{m} p_{ij} = 1,$$

that is, elements of the matrix are non-negative, and each row sums up to 1.

3.2.7 Chapman-Kolmogorov Equation

The time-homogenous property can be extended to calculate the probabilities of transitioning from one state to another in multiple steps i.e. *n-steps*. The n-step transition probabilities can be denoted as

$$\mathbb{P}[X_{n+m} = k | X_m = i] = \mathbb{P}[X_n = k | X_0 = i], \tag{3.6}$$

for $m \geq 0$, since the probability is independent of time. Therefore, we can simplify the n-step transition probability as

$$p_{ij}^{(n)} = \mathbb{P}[X_n = j | X_0 = i], \tag{3.7}$$

for $n, i, j \geq 0$.

The transition probabilities can be calculated by taking matrix powers. For $n = \{1, 2\}$

$$p_{ij}^{(0)} = \begin{cases} 0 & if\ i \neq j, \\ 1 & if\ i = j, \end{cases} \tag{3.8}$$

and

$$p_{ij}^{(1)} = p_{ij}, \tag{3.9}$$

The *Chapman-Kolmogorov Equation* can be denoted in its component form as:

$$p_{ij}^{(n+m)} = \sum_k p_{ik}^{(n)} \times p_{kj}^{(m)}, \tag{3.10}$$

for $n, m \geq 0$ representing the matrix identity

$$\boldsymbol{P}^{(n+m)} = \boldsymbol{P}^{(n)} \times \boldsymbol{P}^{(m)}. \tag{3.11}$$

Assuming $\mathbb{P}[X_0 = i] = p_i > 0$, the derivation of the Chapman-Kolmogorov equation can be computed in the following steps:

$$\mathbb{P}[X_{n+m} = j | X_0 = i]$$

$$= \sum_k \mathbb{P}[X_{n+m} = j, X_n = k | X_0 = i]$$

$$= \sum_k \frac{\mathbb{P}[X_{n+m} = j, X_n = k, X_0 = i]}{\mathbb{P}[X_0 = i]}$$

$$= \sum_k \frac{\mathbb{P}[X_{n+m} = j, X_n = k, X_0 = i]}{p_i}$$

$$= \sum_k \frac{p_i \times p_{ik}^{(n)} \times p_{kj}^{(m)}}{p_i}$$

$$= \sum_k p_{ik}^{(n)} \times p_{kj}^{(m)}$$

$$= p_{ij}^{(n+m)}.$$

The path taken can be expressed as transitioning from state i to the intermediate state k in n-steps represented by the probability $p_{ik}^{(n)}$and then transitioning from state *k* to state *j* in *m-steps* represented by the probability $p_{kj}^{(m)}$.

3.2.8 Types of State States

The possible evolution of a system is limited to the permittable transitions between states in the discrete state space *S*. A state j is said to be *accessible* from state i if

$$\exists\ n \geq 0 : p_{kj}^{(n)} > 0,$$

denoted as

$$i \rightarrow j.$$

$i \rightarrow i$ is the result of $n = 0\ for\ all\ i\ \in S$. If j is accessible from i and i is accessible from j, i.e. $i \rightarrow j$ and $j \rightarrow i$, then i and j *communicate*, denoted as

$$i \leftrightarrow j.$$

Communication is an *equivalence relation*. The three properties of the relation are:

i. $i \leftrightarrow i$ for all i. The relation is *reflexive* since $i \rightarrow i$.

ii. $i \leftrightarrow j$ implies $j \leftrightarrow i$. The relation is *symmetric*.

iii. $i \leftrightarrow k$ and $k \leftrightarrow j$ implies $i \leftrightarrow j$. The relation is *transitive*.

We can take the state space *S* and group all states that communicate with each other into a class known as an *equivalence class*. Two equivalence classes are disjoint. To illustrate, say there exists a state space *S = {A, B, C, D}*. It is observed that in *S*, *A* communicates with *B*, and *C* communicates with *D*. Therefore, two equivalence classes exist, $C_1 = \{A, B\}$ and $C_2 = \{C, D\}$. Transition probabilities between states within the two equivalence classes are observed to be ½. The transition matrix **P** will be:

$$\mathbf{P} = \begin{bmatrix} 1/2 & 1/2 & 0 & 0 \\ 1/2 & 1/2 & 0 & 0 \\ 0 & 0 & 1/2 & 1/2 \\ 0 & 0 & 1/2 & 1/2 \end{bmatrix}.$$

A Markov Chain is *irreducible* if the state space S only has one equivalence class i.e. all states in S communicate with each other. A state i is said to be *absorbing* if it is impossible to transition to another state. A Markov chain is absorbing if it has at least one absorbing state, and if it is possible to transition into an absorbing state from any state in n-steps. Non-absorbing states are known as *transient.* A state i is *recurrent* if the probability of the system returning to i is 1 in n-steps, otherwise the state is transient.

3.3 Estimating Transition Matrices from the Assigned Credit Metric Ratings

The transition probabilities are estimated by

$$\hat{p}_{ij} = \frac{N_{ij}}{N_i}, \tag{3.12}$$

where N_i denotes the number of cooperatives with rating i in the current period and N_{ij} are the number of cooperatives that transitioned from rating i to rating j in the next period.

3.4 The Unconditional Migration Matrix

This study initially estimates one-year migration matrices. Since the dataset spans from 1996 to 2013, 17 one-year migration matrices are estimated. These matrices serve as the initial results of migration behavior on a year to year basis. According to Carty (1997) "an average transition matrix is a concise representation not only of the size, but also the direction of typical rating changes". Transition probabilities can be treated as independent multinomial trials if the Markov chain is assumed to be time-homogenous thereby permitting the aggregation of all annual transition matrices in the sample to obtain the Maximum Likelihood Estimate of a one-year migration matrix (Anderson & Goodman, 1957; Christensen, Hansen, & Lando, 2004).

By modifying equation (3.12) to include a time index t representing the year, the estimate of a one-year transition probability of a cooperative at time t becomes:

$$\hat{p}_{ij}(t) = \frac{N_{ij}(t)}{N_i(t)}, \tag{3.13}$$

and the Maximum Likelihood Estimator (MLE) for the stationary transition probability is denoted as

$$\hat{p}_{ij} = \frac{\sum_{t=0}^{T-1} N_{ij}(t+1)}{\sum_{t=0}^{T-1} N_i\,(t)}, \tag{3.14}$$

where T is the number of years in the sample. MLEs obtained from the entire sample form the unconditional migration matrix. The steady state matrix is estimated from the unconditional migration matrix.

3.5 Assessing Migration Rate Behavior

Leveraging the approaches highlighted in the Literature Review, this study manipulates migration matrices to further assess the migration rate behavior of cooperatives.

3.5.1 Increasing the Time Horizon

Following Altman and Kao (1992b), this study examines the behavior of retention rates as the time horizon increases. This is achieved by estimating an average one-year transition matrix. Next an average two-year migration matrix is estimated followed by an average three-year and so on up until the last period of the sample.

3.5.2 Migration Rate Volatility

The downside of taking the average of migration matrices is that it flattens the year-to-year migration variations caused by exogenous factors such as the state of the economy thereby making it beneficial to observe specific migration behavior on a year-to-year basis (L. V. Carty, 1997). Following Carty (1997), this study tracks the annual fraction of cooperatives downgraded from rating i to rating j, the annual fraction of cooperatives upgraded from rating i to rating j, and the annual fraction of cooperatives retaining the rating to infer rating volatility.

3.5.3 Rating Drift

This study calculates rating drift as defined by Carty (1997) to observe the annual change in overall cooperative credit quality in the dataset. Given a year, the rating drift is denoted as:

$$\frac{\sum Upgraded\ Notches - \sum Downgraded\ Notches}{N} \tag{2.15}$$

where $Upgraded\ Notches$ is the number of notches a cooperative increases by when they upgrade, $Downgraded\ Notches$ is the number of notches a cooperative decreases by when they downgrade, and N is the number of non-defaulted cooperatives in the current period. A positive rating drift indicates an improvement in credit quality while a negative rating drift is a deterioration in credit quality. The value of this metric is that it captures both the direction of change in credit quality in a given year and its relative magnitude.

3.5.4 Rating Activity

According to Carty (1997), rating activity is the "pace at which ratings change, based on units of ratings changed per issuer" and "captures both the effects of multiple rating changes for a single issuer within a given year and the relative sizes of rating changes". Rating activity is denoted as:

$$\frac{\sum Upgraded\ Notches + \sum Downgraded\ Notches}{N} \tag{3.16}$$

where $Upgraded\ Notches$ is the number of notches a cooperative increases by when they upgrade, $Downgraded\ Notches$ is the number of notches a cooperative decreases by when they downgrade, and N is the number of non-defaulted cooperatives in the current period.

3.5.5 Rating Change Magnitude

Another behavioral migration metric that is calculated is the Rating Change Magnitude. It captures the number of rating categories that a transition spans (L. V. Carty, 1997). The metric is used to count the frequency of the various rating change magnitudes in the dataset.

3.5.6 Cooperative Fallen Angel and Rising Star Events

Fallen angels in this study are defined as cooperatives that are downgraded from investment grade to speculative (non-investment) grade. Rising stars are defined as the opposite. Two sub-samples corresponding to the event type are created to study their respective historical trends.

3.5.7 Rating History Dependence

Before we study time dependence, we examine whether a cooperative's prior rating history has an impact on its subsequent rating direction. We do so by considering whether a cooperative was previously upgraded, downgraded or unchanged and then observe the direction of the rating transition in the following period.

3.6 Addressing Time-Period Sensitivity

The migration results of this study are likely sensitive to time-periods. Notable periods with respect to the cooperative industry are as follows:

- 1996–2001: A relatively quiet period. Cooperatives experienced some profitability. Not much growth was observed but cooperatives are pretty stable from a financial perspective in this period.
- 2002–2004: Financial stress experienced in the industry as a result of the Farmland Industries bankruptcy. *"Early 2000s Recession"* likely contributed to the stress during this period.

- 2005–2007: A relatively quiet period. Cooperatives experienced some profitability. Not much growth was observed but cooperatives are pretty stable from a financial perspective in this period.
- 2008 – 2009: There was a large runup in grain prices. Commodity markets experienced extreme volatility due to the *"Great Recession"* and "*Financial Crisis"*.
- 2010 – 2014: Boom times for cooperatives. Cooperatives were very profitable in this period. They grew organically and via mergers. Cooperatives assumed more debt.

This study will estimate conditional migration matrices by creating sub-samples that are conditioned on the stage of the business cycle and the performance of the agricultural sector using Real Net Farm Income as a proxy.

3.6.1 Conditioning on the Business Cycle

Two sub-samples of the dataset are created to study the effects of the business cycle. The sub-samples correspond to expansions and contractions as defined by the National Bureau of Economic Research (NBER). Expansionary periods consist of years 1996, 1997, 1998, 1999, 2000, 2002, 2003, 2004, 2005, 2006, 2007, 2010, 2011, 2012, and 2013. Contractionary periods consist of years 2001, 2008, and 2009. One-period migration matrices are estimated, followed by each sub-sample's average one-period migration matrix.

3.6.2 Conditioning on Real Net Farm Income

To determine the dependence of migration rates on the state of the economy, Nickell et al. (2000) segmented their sample years into three categories—peak, normal times, and trough—which corresponded to the tertiles (three-quantiles) of real GDP growth. This study will not use real GDP growth as it does not best represent the performance of the agricultural sector. Instead, real net farm income (RNFI) will be used in its place. Similar to Nickell et al. (2000), sample years, 1996–2013, are allocated into three categories—peak, normal times, and trough—whereby peak corresponds to sample years with an RNFI above the 75^{th} percentile, trough will correspond to sample years with an RNFI below the 25^{th} percentile, and normal times will correspond to sample years with an RNFI between the 25^{th} and 75^{th} percentiles.

3.7 Measuring the Accuracy of an Estimated Transition Probability

There exists a true population of cooperatives with transition probabilities of p_{ij}. However, the true population is unknown and consequently, $p_{ij}$is also unknown, therefore the standard deviation cannot be determined. The transition probabilities, $\hat{p}_{ij}$, that are calculated in this study are estimators of p_{ij}. Since the transition probabilities $\hat{p}_{ij}$ in a matrix are proportions and are assumed to be independent, the properties of the Binomial Distribution can be adopted to determine how precise $\hat{p}_{ij}$ is by calculating the estimated sampling variance

$$\widehat{var}(\hat{p}_{ij}) = \hat{p}_{ij}(1 - \hat{p}_{ij})/n_i \tag{3}$$

and the estimated standard error

$$\widehat{se}(\hat{p}_{ij}) = \sqrt{\widehat{var}(\hat{p}_{ij})} = \sqrt{\hat{p}_{ij}(1 - \hat{p}_{ij})/n_i} \tag{4}$$

where $\hat{p}_{ij}$ is the probability of transitioning from state i to j, and n_i is the number of cooperatives that started in state i in the sample.

While the standard error is useful in measuring an estimated probability's accuracy, it cannot be used to compare the corresponding estimate elements in sub-sample matrices and therefore a comparative metric is required. The coefficient of variation (CV) is the ratio of the estimated standard error to the estimated transition probability denoted as:

$$\widehat{se}(\hat{p}_{ij})/\hat{p}_{ij} \tag{3.19}$$

The coefficient of variation is measure of relative variability and is used to compare the estimated probabilities between two or more conditioned samples in this study. The larger the coefficient of variation the larger the variation in the estimate. For example, if sub-sample 1 has a CV of 5% and sub-sample 2 has a CV of 12%, then sub-sample 2 has more variation, relative to its mean.

3.8 The Predictive Ability of the Estimated Transition Matrix

Since the probability estimates can be used to predict future distributions this research compares them to observed probabilities from the sample data to determine the accuracy of the prediction. A sub-sample is created using 2014 observations that are removed and treated as out-of-sample observations. Using the sub-sample spanning from 1996 to 2013, an average one-period migration matrix is estimated. The 2013 observations are used to setup the Initial Probability Distribution vector. The Initial Probability Distribution vector is multiplied by the one-year average migration matrix to obtain the predicted 2014 distribution of transition probabilities. The predicted matrix is compared against the actual 2014 distribution.

3.9 Detecting Time-Inhomogeneity

This study calculates the L^2 Norm (Euclidean Distance) to detect time-inhomogeneity. The L^2 Norm is the average root-mean square differences between two matrices. According to Jafry and Schuermann (2004), the L^2 Norm is calculated by

$$L^2 Norm \triangleq \frac{\sqrt{\sum_{i=1}^{S}\sum_{j=1}^{S}\left(P_{A,i,j} - P_{B,i,j}\right)^2}}{S^2} \tag{3.20}$$

where P_A and P_B are $S \times S$ matrices, S is the number of rating categories, and i and j are the rating states. This study calculates the L^2 Norm for every year by comparing the unconditional migration matrix with each one-year migration matrix in the sample. If the series of L^2 Norms are zero or very small then the assumption of time-homogeneity is confirmed but unfortunately it is impossible to determine what is small enough to confirm the assumption (Gunnvald, 2014).

3.10 The Statistical Tests

Following Tan and Yılmaz (2002), this study first tests time-dependence and assumes stationarity. Once the order is determined, stationarity is tested. The authors state that there are three possible outcomes. The first potential outcome is that the order and stationarity are confirmed. The second is that stationarity is rejected after determining the order. According to Tan and Yılmaz, the consequence of this outcome is that the order cannot be determined by Markov chains using the sample as is. They suggest dividing it into smaller sub-samples, repeating the test until stationarity is confirmed. However, there are not enough observations to split the sub-samples into even smaller sub-samples with the hope of identifying time-homogeneity. Therefore, if time-homogeneity is rejected after confirming the order of the process, the conclusion of the test will be “time-heterogenous, order inconclusive”. The last possibility mentioned by the authors is that the test is “inconclusive” if the order of the chain cannot be determined. This is because testing for stationarity is only necessary if the order is known.

3.10.1 The Time-Dependence Test

The purpose of the time-dependence test is to confirm the validity of the assumption that the process is first-order. According to Tan and Yılmaz (2002), the steps are to test two sequential orders at a time. The last order to test is set by the researcher. The test begins with testing the zero-order process with the first-order and ending the procedure when the result is do not reject. A stochastic process is first-order if one rejects zero-order against first-order and fails to reject first-order against second-order. The hypotheses are:

$$H_0\colon \forall i\colon p_{ij} = p_j$$

$$H_A\colon \exists i\colon p_{ij} \neq p_j$$

where $p_{ij}$is the probability of transitioning from state i to j estimated from the entire sample, and p_j is the probability of a cooperative transitioning to rating j estimated from the entire sample. The Pearson χ^2 Test and the Likelihood Ratio Test are used.

The Pearson χ^2 Test for evaluating the first-order Markov property is denoted as

$$Q^{(O(0))} = \sum_{i=1}^{S}\sum_{j=1}^{S} n_i \frac{(\hat{p}_{ij} - \hat{p}_j)^2}{\hat{p}_j} \sim asymptotically \boldsymbol{\chi}^2((s-1)^2) \tag{5}$$

where n_i is the total number of cooperatives that transitioned from rating i over the entire sample, p_{ij} is the probability of transitioning from state i to j estimated from the entire sample, p_j is the probability of transitioning to state j estimated from the entire sample and is assumed that $p_j > 0$. $Q^{(O(0))}$ has a chi-squared distribution with $(s-1)^2$ degrees of freedom.

The Likelihood Ratio Test for evaluating the first-order Markov property is denoted as

$$LR^{(O(0))} = 2\sum_{i=1}^{S}\sum_{j=1}^{S} n_{ij}\, ln \frac{\hat{p}_{ij}}{\hat{p}_i} \sim asymptotically \boldsymbol{\chi}^2((s-1)^2) \tag{6}$$

where n_{ij} is the total number of cooperatives that transitioned from rating i to j over the entire sample, $p_{ij}$is the probability of transitioning from state i to j estimated from the entire sample, p_i is the probability of transitioning from state i estimated from the entire sample, and $p_i > 0$. $LR^{(O(0))}$ has a $\boldsymbol{\chi}^2$ distribution with $(s-1)^2$ degrees of freedom.

The second-order Markov chain considers a cooperative transitioning to state j in time $t+1$ given it was in state h in time $t-1$ and state i in time t. Since the matrix is two dimensional, the transition to state i from h is thought of as a composite state (Anderson &

Goodman, 1957; Basawa & Rao, 1980) and will represent the initial state in the matrix. The hypotheses to test the second-order Markov chain are:

$$H_0: \forall h: p_{hij} = p_{ij}$$

$$H_A: \exists h: p_{hij} \neq p_{ij}$$

The Pearson χ^2 Test for evaluating the second-order Markov property is denoted as

$$Q^{(O(1))} = \sum_{h=1}^{S} \sum_{i=1}^{S} \sum_{j=1}^{S} n_{hi} \frac{(\hat{p}_{hij} - \hat{p}_{ij})^2}{\hat{p}_{ij}} \sim asymptotically \boldsymbol{\chi}^2(s(s-1)^2) \qquad (3.23)$$

where n_{hi} is a composite state that represents the total number of cooperatives that transitioned from rating h in time $t-1$ to rating i in t over the entire sample, $p_{hij}$is the probability of a cooperative transitioning to state j in $t+1$ given it was in state h in time $t-1$ and i in t estimated from the entire sample, $p_{ij}$is the probability of transitioning from state i in time t to j in $t+1$ estimated from the entire sample. $Q^{(O(1))}$ has a $\boldsymbol{\chi}^2$ distribution with $s(s-1)^2$ degrees of freedom.

The Likelihood Ratio Test for evaluating the second-order Markov property is denoted as

$$LR^{(O(1))} = 2 \sum_{h=1}^{S} \sum_{i=1}^{S} \sum_{j \in C_{hi}} n_{hij} \, ln \frac{\hat{p}_{hij}}{\hat{p}_{ij}} \sim asymptotically \boldsymbol{\chi}^2(s(s-1)^2) \qquad (3.24)$$

where $C_{hi} = \{j: \hat{p}_{hij} > 0\}$ is the set of non-zero transition probabilities in the hi-th row of the average transition matrix estimated from the entire sample, $C_i = \{j: \hat{p}_{ij} > 0\}$ is the set of non-zero transition probabilities in the i-th row of the average transition matrix estimated from the entire sample, n_{hij} represents the total number of cooperatives that transitioned to j given they were in rating h in time $t-1$ and rating i in t over the entire sample—again hi is a composite state, $p_{hij}$is the probability of a cooperative transitioning to state j in $t+1$ given it was in state h

in time $t-1$ and i in t estimated from the entire sample, and p_{ij} is the probability of transitioning from state i to j estimated from the entire sample, c_i is the number of elements in C_i, $D_i = \{h: n_{hi} > 0\}$ is the set of non-zero transition frequencies from composite state hi in the i-th row of the average transition matrix estimated from the sample, and d_i is the number of elements in D_i. $LR^{(O(1))}$ has a $\boldsymbol{\chi}^2$ distribution with $s(s-1)^2$ degrees of freedom.

3.10.2 The Test for Time-Homogeneity

Following Bickenbach and Bode (2003), the sample comprising of T transitions will be divided into M mutually exclusive and exhaustive sub-samples ($m = 1, 2, \dots, M; M \leq T$) and the average migration matrices from each sub-sample is compared against the sample's unconditional migration matrix to determine if the difference is significant. The hypotheses as proposed by Anderson and Goodman (1957) are:

$$H_0\colon \forall m\colon p_{ij|m} = p_{ij}$$

$$H_A\colon \exists m\colon p_{ij|m} \neq p_{ij}$$

where $p_{ij|m}$ is the probability of transitioning from state i to j that is estimated from the entire sub-sample m, and $p_{ij}$is the probability of transitioning from state i to j that is estimated from the entire sample. The Pearson χ^2 and the Likelihood Ratio Tests will be used.

The Pearson χ^2 Test for evaluating stationarity is denoted as:

$$Q^{(M)} = \sum_{m=1}^{M} \sum_{i=1}^{S} \sum_{j \in A_i} n_{i|m} \frac{(\hat{p}_{ij|m} - \hat{p}_{ij})^2}{\hat{p}_{ij}} \sim asymptotically \boldsymbol{\chi}^2 \left(\sum_{i=1}^{S} (a_i - 1)(b_i - 1) \right) \tag{3.25}$$

where $A_i = \{j: \hat{p}_{ij} > 0\}$ is the set of non-zero transition probabilities in the i-th row of the average transition matrix estimated from the sample, $n_{i|m}$ is the total number of cooperatives that transitioned from rating i over the entire time period in the m-th sub-sample, $\hat{p}_{ij|m}$ is the probability of transitioning from state i to j that is estimated from the entire time period of the m-th sub-sample, $\hat{p}_{ij}$ is the probability of transitioning from state i to j that is estimated from the entire sample, a_i is the number of elements in A_i, and b_i is the number of sub-samples that have at least one cooperative in the i-th row i.e. $B_i = \{m: n_{i|m} > 0\}$. $Q^{(M)}$has a $\boldsymbol{\chi}^2$ distribution with $(a_i - 1)(b_i - 1)$ degrees of freedom.

The Likelihood Ratio Test for evaluating stationarity is denoted as

$$LR^{(M)} = 2\sum_{m=1}^{M}\sum_{i=1}^{N}\sum_{j\in A_i|m} n_{ij|m} ln\frac{\hat{p}_{ij|m}}{\hat{p}_{ij}} \sim asymptotically \boldsymbol{\chi}^2\left(\sum_{i=1}^{N}(a_i - 1)(b_i - 1)\right) \tag{7}$$

where $A_{i|m} = \{j: \hat{p}_{ij|m} > 0\}$ is the set of non-zero transition probabilities in the i-th row of the average transition matrix estimated from the m-th sub-sample, $n_{ij|m}$ is the total number of cooperatives that transitioned from rating i to j over the entire time period in the m-th sub-sample, $\hat{p}_{ij|m}$ is the probability of transitioning from state i to j estimated from the entire time period of the m-th sub-sample, $\hat{p}_{ij}$ is the probability of transitioning from state i to j estimated from the entire sample, a_i is the number of elements in A_i, and b_i is the number of sub-samples that have at least one cooperative in the i-th row i.e. $B_i = \{m: n_{i|m} > 0\}$. $LR^{(m)}$ has a $\boldsymbol{\chi}^2$ distribution with $(a_i - 1)(b_i - 1)$ degrees of freedom.

Chapter 4 - Data

4.1 Data Description

This study used proprietary, fiscal year-end financial statement data from agricultural cooperatives provided by CoBank. The cooperatives in the sample have loans with CoBank. The sample data was restricted from 1996 to 2013, and 2014 observations were used for out-of-sample forecast evaluation. To confirm the accuracy of the financial statements, a reconciliation of the income statement and balance sheet was conducted.

This study does not assume why a cooperative ceases to be included in the dataset. Any instances of cooperatives that were not observed annually throughout the dataset were removed. Instances of cooperatives changing their reporting dates and SIC Group Description (Farm Supply/Marketing and Grain Marketing) were removed. Initially the sample consisted of 162 agricultural cooperatives. The previous steps resulted in the elimination of 7 cooperatives from the panel dataset. The final dataset consisted of 155 cooperatives to study; equivalently this translated to 2,790 firm years. In the final set, 133 cooperatives were Farm Supply/Marketing while 22 were Grain Marketing, according to the SIC Group Description.

Net Farm Income (NFI) was obtained from the United States Department of Agriculture Economic Research Service (ERS), updated as of March 6th, 2019. Only annual observations of NFI from 1996 to 2014 were used. Annual observations of the average Effective Federal Funds Rate corresponding to the sample years were obtained from the Federal Reserve Bank of St. Louis.

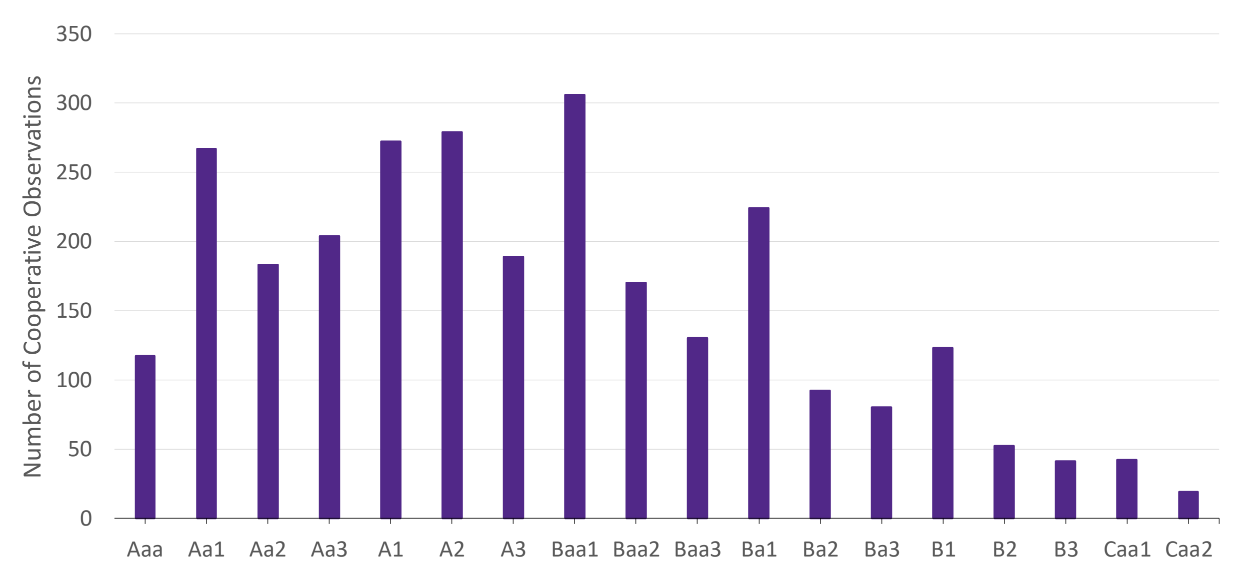
4.2 Summary Statistics

Most cooperatives in the CoBank data are relatively small. Of the 2,790 firm years in the 19962013 sample, 1,375 (49.28%) had less than $25 million in sales, 576 (20.65%) had $25 to

$50 million in sales, and 839 (30.07%) had sales of more than $50 million. Compared to smaller firms, larger entities tend to be less adversely affected to normal business challenges or recessions (Psillaki, Tsolas, & Margaritis, 2010).

All 18 rating categories with the numerical modifiers were classified in the dataset. The distribution of the ratings was right skewed (Figure 4.1). Most cooperatives in the sample were investment grade (i.e. Aaa–Baa3). The granularity of the 18-class rating scale was able to capture the smaller differences in rating quality. There were more Aa1 rated cooperatives than there were Aaa, Aa2, and Aa3. The average rating of a cooperative using the 18-class rating scale was Baa1.

Figure 4.1 Distribution of Credit Metric Ratings with Numeric Modifier



Seven rating classes remained after eliminating the numeric modifiers (Figure 4.2). Again, the distribution was right skewed. There were far fewer Aaa rated cooperatives than Aa, A, and Baa. Cooperatives rated A had the highest frequency in the sample followed by Aa then Baa. Only 61 cooperatives were rated Caa. The average rating of a cooperative on the 7-class rating scale was Baa.

Figure 4.2 Distribution of Credit Metric Ratings without Numeric Modifier

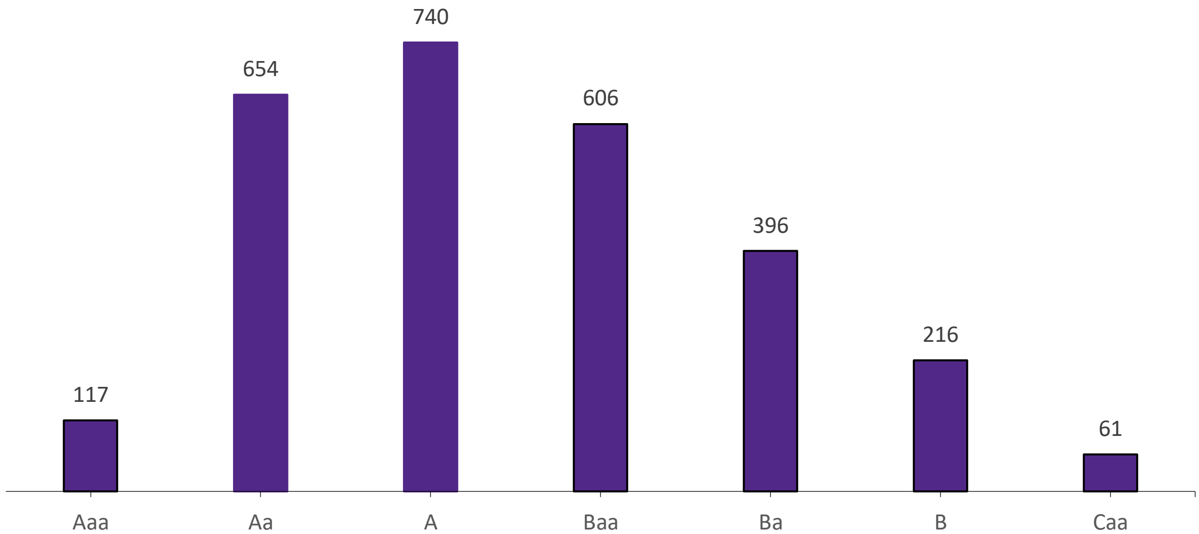


Figure 4.3 illustrates the distribution of the locations of the cooperatives. Illinois and Kansas each had 26 cooperatives, the highest in the sample, followed by Iowa with 23. The lowest frequency observed was 1 cooperative in California, Florida, Mississippi, Pennsylvania, South Dakota, and Virginia.

Figure 4.3 Distribution of Cooperative Locations

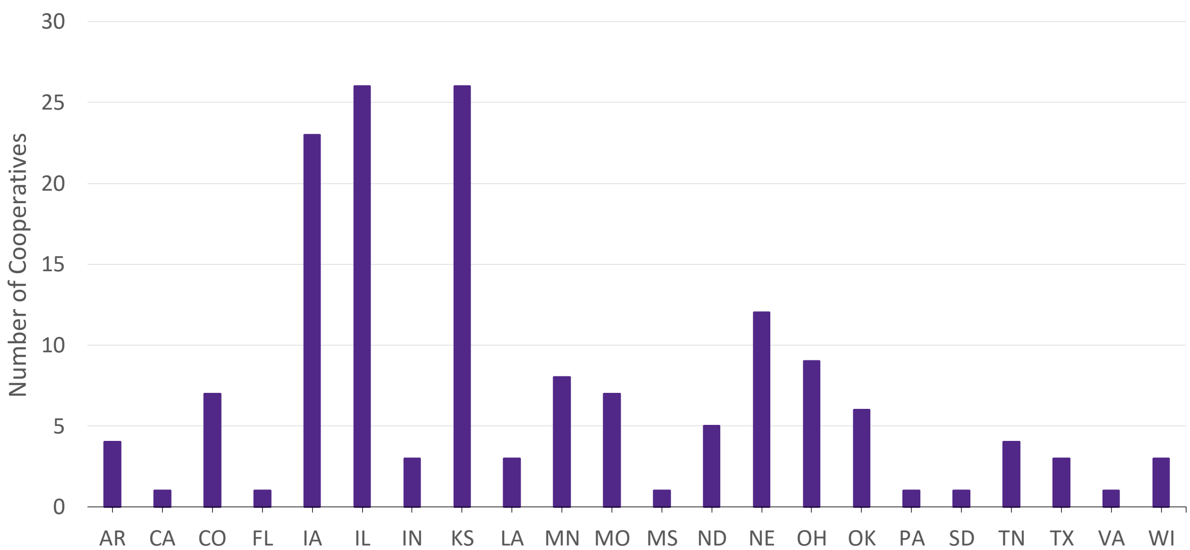


Figure 4.4 illustrates the annual frequency of ratings and RNFI. Annual frequencies of Aaa and Caa rated cooperatives are low relative to other ratings. Cooperatives rated Aa declined in frequency to 2008 with some variation, increased from 13 in 2008 to 55 in 2009, decreased in 2011, and increased thereafter. Non-investment grade cooperatives increased in frequency from 1997 to 2003, declined in 2004 and 2005, and decreased from 2006 to 2008. Figure 4.4 also indicates that there is no clear relationship between the ratings and RNFI.

Figure 4.4 Annual Frequency of Ratings and Real Net Farm Income, 1996–2013

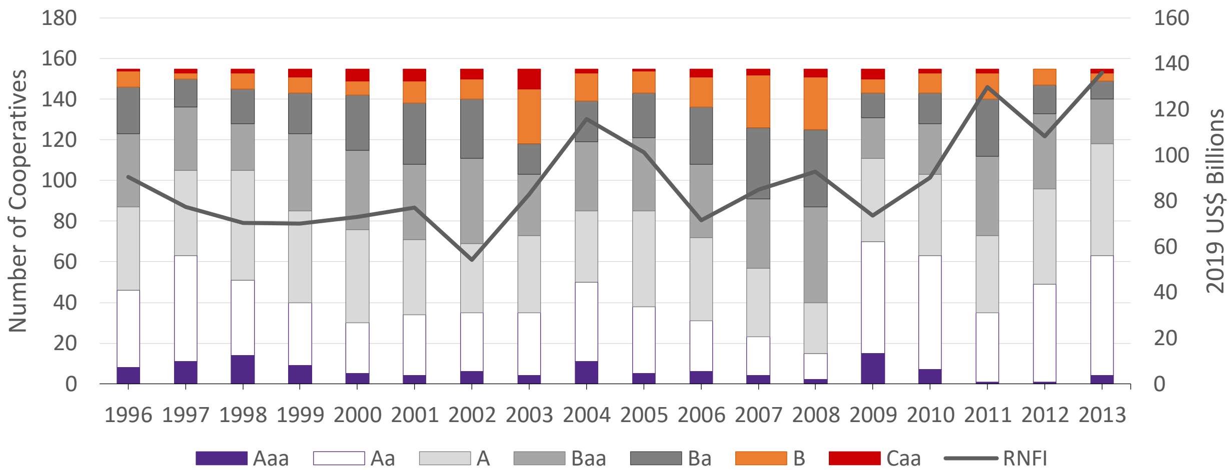
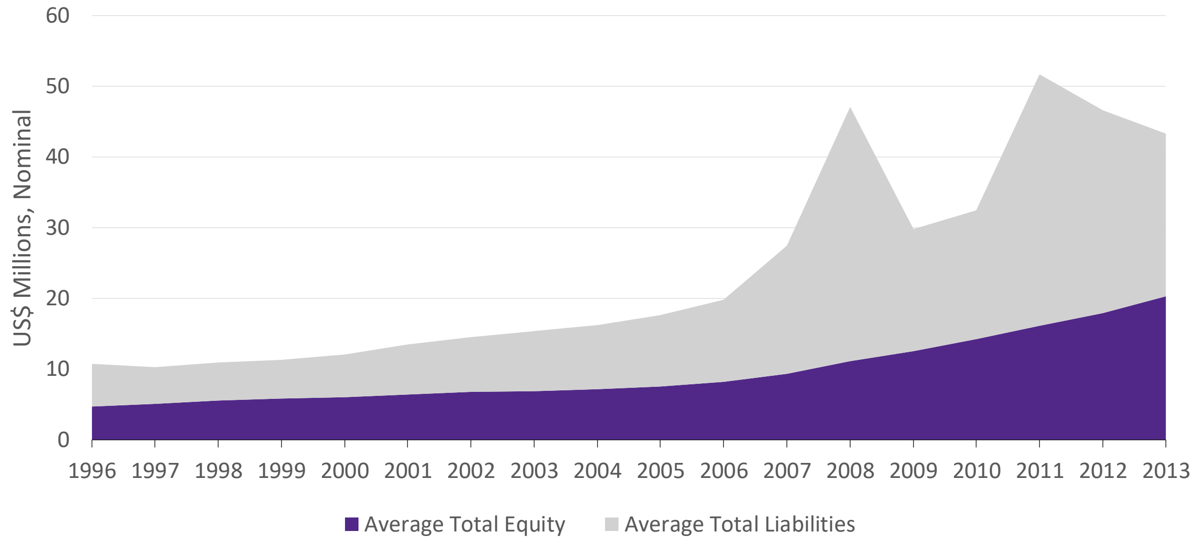


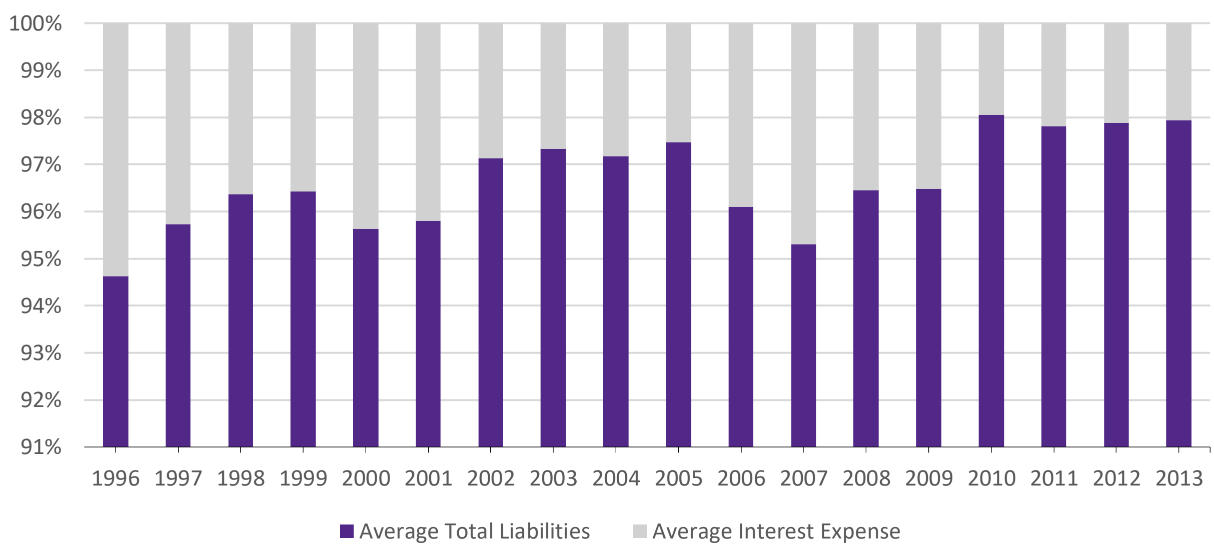
Figure 4.5 illustrates the average balance sheet over time. The average total assets across the sample was $23.95 million, average total liabilities was $14.41 million, and the average total equity was $9.54 million. The balance sheet increased over time. The spikes in average total liabilities were a result of increased commodity market volatility. The amount of seasonal loans increased to meet margin calls in addition to increased capital investment thereby driving long-term debt. Average total equity did not experience any variation and trended upwards throughout the sample time period.

Figure 4.5 The Average Balance Sheet Over Time



Average interest expense relative to average total debt as shown in Figure 4.6 was at its highest in 1996. Interest expense trended downwards thereafter and increased in 2000. It trended downwards again the following year until 2005. It sharply increased again 2006 and increased further in 2007. 2008 to 2010 saw a decreasing trend in interest expense and it levelled off thereafter.

Figure 4.6 Average Total Liabilities and Average Interest Expense Over Time



To assess the representativeness of the data used in this study, average financial metrics from the CoBank data were compared to agricultural cooperative data from the USDA (Table 4.1). The similarity of the two sets of metrics indicated that the CoBank data is representative of the national sample. "The representativeness of the CoBank data is unsurprising as CoBank has a national charter to lend to agricultural cooperatives, as well as strong market share in the cooperative sector" (Smart, Briggeman, Tack, & Perry, 2019).

Table 4.1 Comparison of Average 2014 CoBank and United States Department of Agriculture (USDA) Agricultural Cooperative Financial Data

Variable	CoBank Data	USDA Data
Total Assets	$43,858,266	$41,349,953
Total Liabilities	$21,434,810	$23,498,101
Total Equity	$22,423,456	$17,851,852
Total Sales	$116,982,551	$114,128,443
Cost of Goods Sold	$108,864,314	$104,573,837
Gross Margin	$8,118,237	$9,554,558
Total Expenses	$5,502,886	$6,484,378
Net Income	$2,615,351	$3,070,180
Number of Cooperatives	155	2,106

Sources: CoBank Risk Analyst Database and USDA Cooperative Data

Chapter 5 - Results

5.1 Unconditional Migration Matrix Analysis

The unconditional migration matrix was calculated by first constructing the total count of every one-year transition in the 1996–2013 sample. The probabilities were then estimated by dividing each element by their respective row sums. The estimates from the unconditional sample are expected to be the best Maximum Likelihood estimators of the possible rating transitions.

5.1.1 The One-Year Average Migration Matrix

A migration matrix represents the change in credit rating of a cooperative from its original rating in the current period to the terminal rating in the next period. Each row of the matrix represents the original rating and each column represents the terminal rating. Table 5.1 reports the count of transitions between ratings over the entire 1996–2013 sample. The sum of the elements in a given row, i, indicate the total number of cooperatives that are rated i in the current period. The sum of the elements in a given column, j, indicate the total number of cooperatives that transitioned to rating j in the next period. Most migrations occurred among investment grade ratings i.e. Aaa, Aa, Aa, and Baa. The highest transition frequency in the sample was the retention of the Aa rating (296), followed by retaining the A rating (283). As the original rating decreased in credit quality, the frequency of being downgraded to Caa increased. The frequency of retaining the Aaa rating is lower than being downgraded to Aa since the expectation is to observe the largest frequencies along the diagonal. There was one more upgrade event than retention events for Ba rated cooperatives, and cooperatives rated Caa experienced more upgrade events than retention events.

Table 5.1 Unconditional One-Year Total Count Migration Matrix, 1996–2013

	Terminal Rating						
Original Rating	Aaa	Aa	A	Baa	Ba	B	Caa
Aaa	39	43	24	6	1	0	0
Aa	45	296	138	73	33	10	0
A	16	160	283	158	53	12	3
Baa	9	70	167	181	110	40	7
Ba	0	31	58	110	109	65	14
B	0	15	27	36	53	60	21
Caa	0	1	2	6	14	21	15

The probabilities of transitioning from rating i to rating j are obtained by taking each transition frequency from Table 5.1 and dividing it by its corresponding row sum. Table 5.2 illustrates the unconditional one-year average transition probabilities estimated over the entire 1996–2013 sample. Stability refers to the likelihood of a cooperative maintaining its rating in the next period. Volatility increases as stability decreases. Aa (49.75%) and A (41.31%) rated cooperatives were more stable than those rated Aaa (34.51%) over a one-year time horizon since cooperatives rated Aa and A had higher probabilities than cooperatives rated Aa. Increasing volatility as credit quality decreases is not strictly observed across all seven rating classes. Volatility strictly increases from Aa to Ba only, while B (28.30%) rated cooperatives are slightly more stable than Ba (28.17%), and those rated Caa (25.42%) are the most volatile as expected. Monotonicity is observed in the estimates since the probability of migrating to another class decreases the further away it is.

Table 5.2 Unconditional One-Year Average Migration Matrix, 1996–2013

	Terminal Rating						
Original Rating	Aaa	Aa	A	Baa	Ba	B	Caa
Aaa	34.51%	38.05%	21.24%	5.31%	0.88%	0.00%	0.00%
	(4.47%)	(4.57%)	(3.85%)	(2.11%)	(0.88%)	(0.00%)	(0.00%)
Aa	7.56%	49.75%	23.19%	12.27%	5.55%	1.68%	0.00%
	(1.08%)	(2.05%)	(1.73%)	(1.34%)	(0.94%)	(0.53%)	(0.00%)
A	2.34%	23.36%	41.31%	23.07%	7.74%	1.75%	0.44%
	(0.58%)	(1.62%)	(1.88%)	(1.61%)	(1.02%)	(0.50%)	(0.25%)
Baa	1.54%	11.99%	28.60%	30.99%	18.84%	6.85%	1.20%
	(0.51%)	(1.34%)	(1.87%)	(1.91%)	(1.62%)	(1.05%)	(0.45%)
Ba	0.00%	8.01%	14.99%	28.42%	28.17%	16.80%	3.62%
	(0.00%)	(1.38%)	(1.81%)	(2.29%)	(2.29%)	(1.90%)	(0.95%)
B	0.00%	7.08%	12.74%	16.98%	25.00%	28.30%	9.91%
	(0.00%)	(1.76%)	(2.29%)	(2.58%)	(2.97%)	(3.09%)	(2.05%)
Caa	0.00%	1.69%	3.39%	10.17%	23.73%	35.59%	25.42%
	(0.00%)	(1.68%)	(2.36%)	(3.93%)	(5.54%)	(6.23%)	(5.67%)

The standard error indicates the reliability of the estimate in representing the transition probability of the population (Table 5.2). The standard errors of the estimates indicated that the probabilities of retaining Aa (2.05%), A (1.88%), Baa (1.91%), and Ba (2.29%) ratings were more reliable than the estimates of retaining Aaa (4.47%), B (3.09%), and Caa (5.67%) ratings since they were relatively smaller. Not including Aaa, the small standard errors were a result of the high frequency of observations retaining an investment grade and the Ba rating since a larger sample size decreases standard error.

There were numerous instances of cooperatives making transitions of three or more rating classes. A change in credit rating indicates a degree of instability so it follows that large rating changes correspond to large instabilities. Most cooperatives in the sample are relatively small in size. There are two important implications of a cooperative being small. Firstly, smaller cooperatives are unlikely to be as diversified as larger cooperatives. Cooperatives that are not adequately diversified are unable to eliminate unsystematic risk. The scale also suggests that they are less likely to be geographically diversified. This means localized events such as drought or adverse weather events can severely impair a cooperative's revenues. The characteristics of the cooperatives that experienced large rating changes are investigated. Table 5.3 shows the frequencies and proportions of cooperatives that changed by three or more ratings. Most cooperatives that changed by three or more ratings had sales of less than $25 million (61.11%), representing 28.39% of cooperatives in the 1996–2013 sample. The large rating changes observed indicate how sensitive some cooperatives were to the risks they were exposed to in their respective operations.

Table 5.3 Cooperatives Changing by 3 Ratings or More

Sales Size	Frequency	Proportion	% of Cooperatives
<$25M	44	61.11%	28.39%
$25M-$50M	13	18.06%	8.39%
$50M+	15	20.83%	9.68%

5.1.2 The Steady State

Assuming the Markov property and stationarity assumptions hold, cooperatives are more likely to transition to a prime rating in the long-run. The transition probabilities in Table 5.4 indicate the limiting values of possible transitions as time approaches infinity. Cooperatives are more likely to transition to rating A (27.00%). The second most likely transition is rating Aa (24.00%) followed by rating Baa (21.00%). Downgrading or maintaining the Caa (2.00%) rating was the least likely transition state in the 1996–2013 sample.

Table 5.4 The Steady State of Agricultural Cooperatives, 1996–2013

	Terminal Rating						
Original Rating	Aaa	Aa	A	Baa	Ba	B	Caa
Aaa	4.00%	24.00%	27.00%	21.00%	14.00%	8.00%	2.00%
Aa	4.00%	24.00%	27.00%	21.00%	14.00%	8.00%	2.00%
A	4.00%	24.00%	27.00%	21.00%	14.00%	8.00%	2.00%
Baa	4.00%	24.00%	27.00%	21.00%	14.00%	8.00%	2.00%
Ba	4.00%	24.00%	27.00%	21.00%	14.00%	8.00%	2.00%
B	4.00%	24.00%	27.00%	21.00%	14.00%	8.00%	2.00%
Caa	4.00%	24.00%	27.00%	21.00%	14.00%	8.00%	2.00%

5.1.3 Multi-Year, Average Rating Transition Matrices

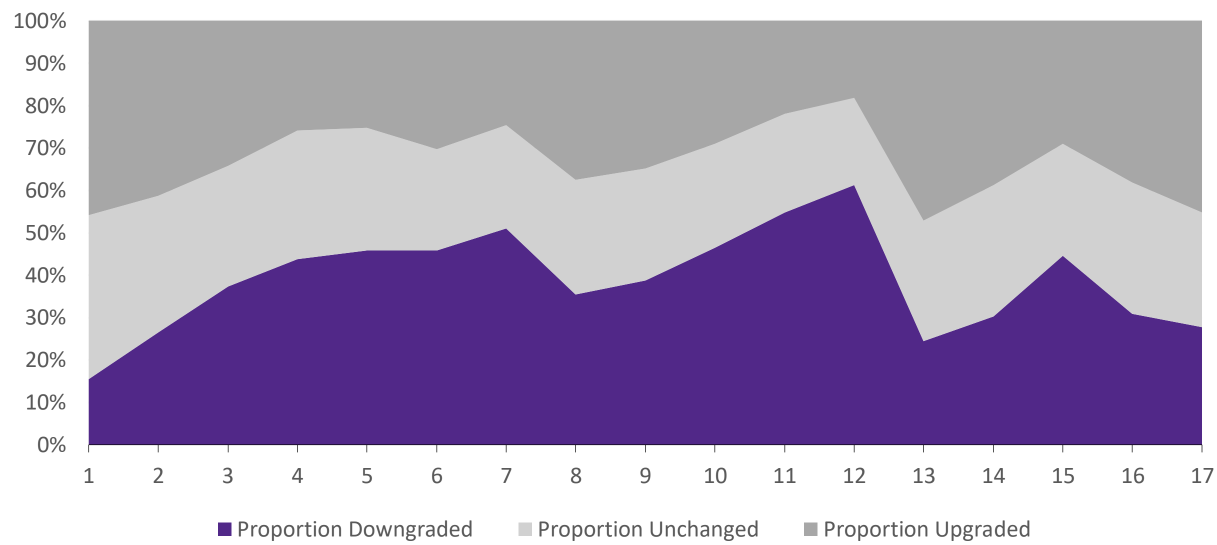
Average migration matrices were calculated for each time horizon using the 1996–2013 sample. Table 5.5 shows the retention rates for the first five time horizons. Migration matrices for the first five time horizons can be found in Table A.2 of the appendix. Cooperatives mostly experienced a trend of declining retention rates as the time horizon increased for the first five years. The probabilities of remaining unchanged in the next period did not decrease strictly with decreasing credit rating across all time horizons. Aaa rated cooperatives were more volatile than those rated Aa and A across all time horizons. That is, Aa and A rated cooperatives were the most stable as the time horizon increased. Baa rated cooperatives were more stable than those rated Aaa from the two-year to five-year horizon. Caa rated cooperatives showed a pattern of being more likely to be upgraded with increasing time horizon.

Table 5.5 Retention Rate Behavior with Increasing Time Horizon

Time Horizon	Aaa	Aa	A	Baa	Ba	B	Caa
1	34.51%	49.75%	41.31%	30.99%	28.17%	28.30%	25.42%
2	26.79%	40.77%	36.99%	28.52%	21.18%	25.98%	18.64%
3	23.42%	38.79%	33.50%	29.72%	20.87%	29.84%	21.05%
4	18.27%	38.29%	33.21%	26.50%	23.94%	23.76%	16.36%
5	23.60%	36.32%	31.41%	29.16%	25.16%	24.14%	12.00%

Figure 5.1 shows the annual proportions of rating changes with increasing time horizon across the entire 1996-2013 sample. As the time horizon increased, the proportion of cooperatives downgraded increased up to the seventh year. The seventh and eighth year showed a decrease in the downgrade proportion, but the proportion continued to increase thereafter and subsequently fell again in the 12th year. Retention rates rose again but to a lower proportion and tapered downwards after. Retention rates generally decreased for the first 12 years but widened after and maintained stability. The decrease in retention rates observed for the first 12 years are in line with expectations. As the time horizon increases, volatility likely increases and the likelihood of retaining the original rating decreases.

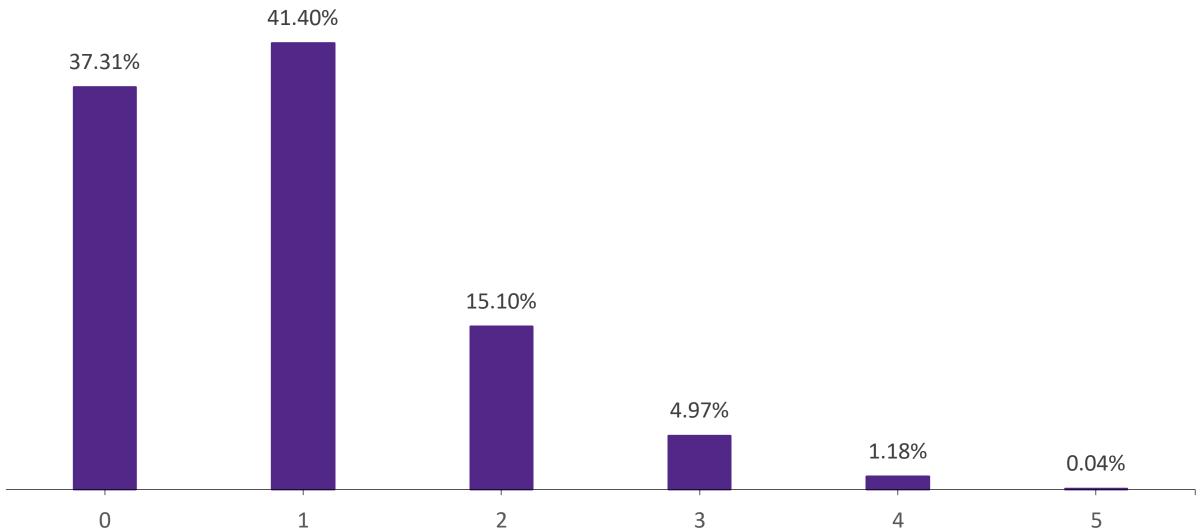
Figure 5.1 Proportions of Rating Changes for 1 Through 17-Year Time Horizons



5.1.4 Rating Change Magnitude

Upgrades occurred more frequently than downgrades in the 1996–2013 sample; 31.92% of cooperatives upgraded and 30.78% downgraded. Rating change magnitude was calculated to assess the frequencies of the size of the migrations. The magnitude is the number of rating classes a cooperative changed by when it transitioned from one rating to the other. Cooperatives were more likely to experience a change of one notch. Of the cooperatives in the sample, 37.31% of cooperatives did not experience a rating change while 41.40% changed by one notch (Figure 5.2 %). For a magnitude of one and greater, the likelihood of a smaller magnitude is higher than a larger change with 15.10% of cooperatives changing by two notches and 4.97% changing by three.

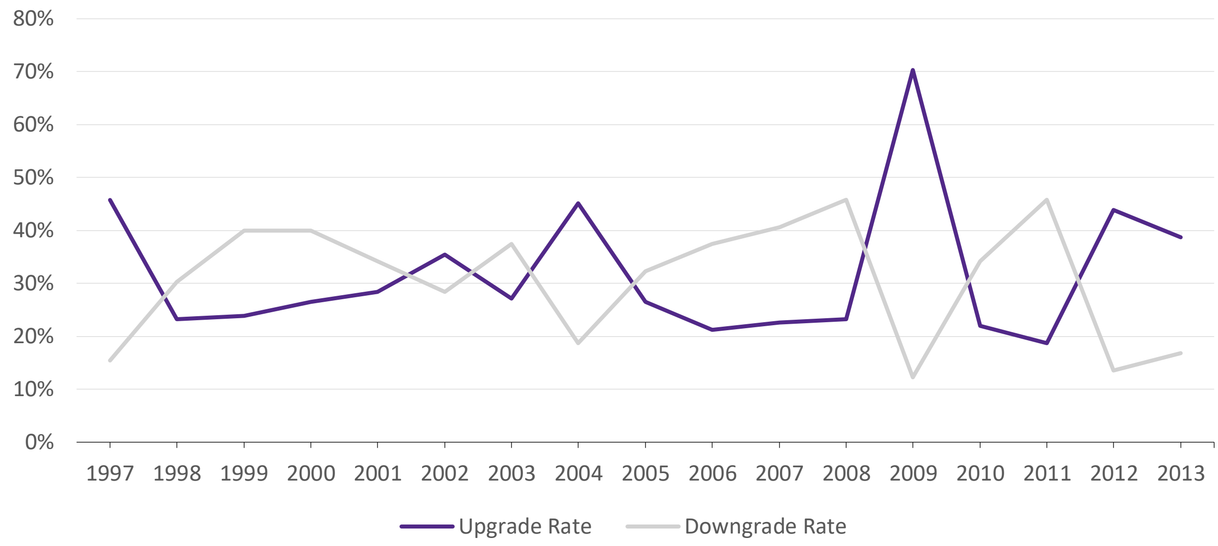
Figure 5.2 Frequency of Credit Metric Rating Changes of Various Magnitudes, 1996–2013



5.1.5 Migration Rate Volatility

To correct the smoothing effect of averaging transition probabilities, year-to-year rating volatility was measured. Cooperatives were more likely to be downgraded than upgraded for most of the sample period (Figure 5.3). The average proportion of cooperatives downgraded across the sample was 38.86% and the average proportion of cooperatives upgraded was 33.32%. The upgrade rate was the largest in 2009 and the downgrade rate was the lowest in the same year. The largest change in the upgrade rate occurred from 2008 to 2009 where 70.32% of cooperatives were upgraded in 2009. The 2004–2008 period saw a prolonged increase in downgrade rates and surpassed upgrade rates in 2005. The annual proportion of cooperatives downgraded increased again from 2009 to 2011 reaching 45.81% and fell to 13.55% in 2012.

Figure 5.3 Yearly Fraction of Upgraded and Downgraded Cooperatives



5.1.6 Trends in Credit Quality From 1996 to 2013

Although a simple comparison between the frequency of upgrades and downgrades on an annual basis is insightful in measuring general volatility, a more descriptive measurement can be taken by considering the magnitude of the rating change. Average notch-weighted upgrades and downgrades reflect the relative frequency of the rating change and also describe their relative size in notches. Figure 5.4 illustrates the annual experience of average notch-weighted upgrades and downgrades along with RNFI. The average notch size of a rating change across the sample 0.46. The size of average notch-weighted upgrades was 0.47 across the sample and 0.45 for average notch-weighted downgrades. The relationship between average notch-weighted changes in ratings and the RNFI was examined by calculating the correlation coefficient. The correlation of -0.00698 indicated that average upgraded notches did not have a relationship with RNFI. The average downgrade notches had a weak negative relationship with a correlation of -0.112. The average notch-weighted changes had stronger relationships with the Effective Federal Funds Rate (EFFR). The average notch-weighted upgrades and average notch-weighted downgrades had correlation values of -0.394 and 0.262 respectively.

Figure 5.4 Historical Trends of Notch-Weighted Upgrades and Downgrades

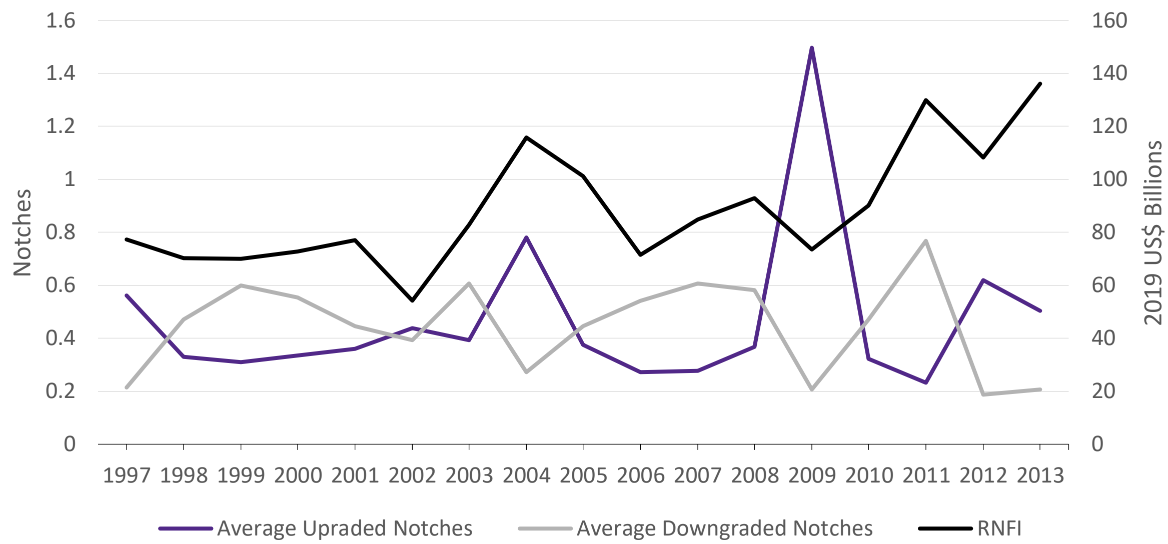
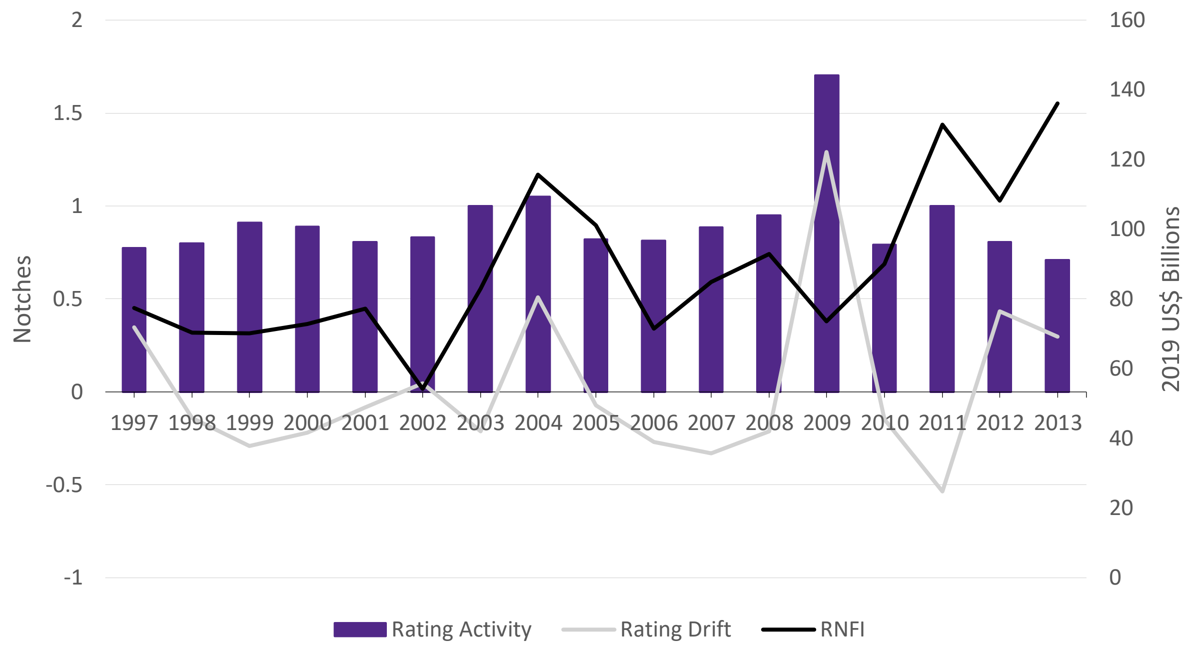


Figure 5.5 illustrates the annual changes in rating drift and rating activity along with historical RNFI. Rating drift is negative when average notch-weighted downgrades exceed average notch-weighted upgrades and reflect a decrease in credit quality. Most sample years experienced negative rating drift since periods where notch-weighted upgrades exceeding equivalently weighted downgrades were short-lived. Credit quality deteriorated by more than half a notch from 2003 to 2004 and deteriorated from 2004 to 2007, falling by 0.84 notches. There was a rapid improvement from 2007 to 2009 as cooperatives increased their ratings by 1.62 notches on average during that period. Credit quality collapsed by 1.83 notches from 2009 to 2011 but improved thereafter by 0.83 notches.

Figure 5.5 Historical Trends of Rating Drift and Rating Activity

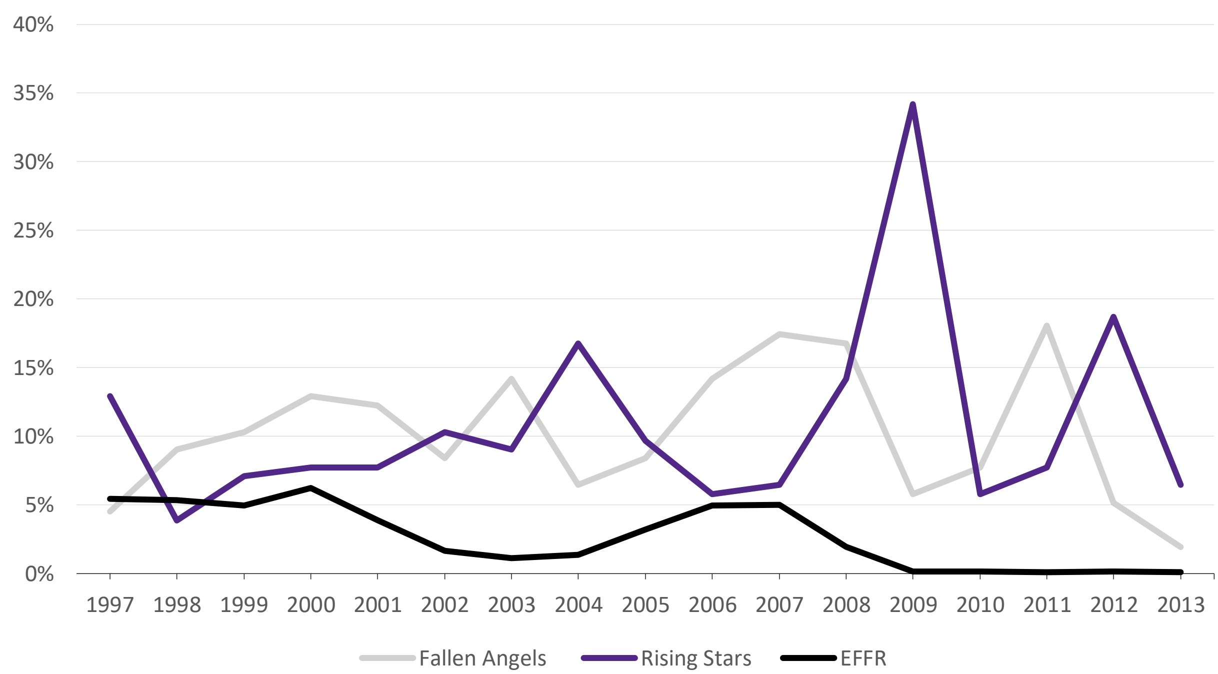


Rating drift had little relationship with RNFI with a correlation of 0.0420 and a correlation of -0.375 with the Effective Federal Funds Rate. A strong positive relationship was observed between rating drift and rating activity as the correlation coefficient was 0.610. The difference between calculating rating drift and rating activity is that rating drift takes the difference of average notch upgrades and average notch downgrades whereas rating volatility aggregates the two. Rating drift and rating activity were possibly being influenced by average notch-weighted upgrades. The correlation between rating drift and average notch-weighted upgrades was 0.955 indicating a very strong positive relationship. The correlation between rating activity and the average notch-weighted upgrades was 0.816. Excluding 2009, rating activity across the sample period was relatively stable with small increases and decreases in average notch changes. It was evident that the 2009 spike in rating activity was primarily driven by increased average notch-weighted upgrades since it coincided with the sharp increase in rating drift during the same year.

5.1.7 Cooperative Fallen Angel and Rising Star Events

Figure 5.6 illustrates the historical rates of fallen angels, rising stars and the Effective Federal Funds Rate. Fallen angel events are instances when cooperatives are downgraded from investment grade to non-investment grade while rising stars are cooperatives that have been upgraded from non-investment grade to investment grade. The average fallen angel rate across the sample was 10.21% and the average rising star rate was 10.85%. Rising star rates moved in opposite directions to the Effective Federal Funds Rate in most periods. The correlation coefficient between the two was -0.425, a moderate negative relationship between rising star rates and Effective Federal Funds Rate. Fallen angel rates showed a weak positive relationship with Effective Federal Funds Rate with a correlation of 0.256. Rising star rates were more subdued than fallen angel rates from 1997 to 2003. A sharp uptick in rising star events occurred in 2004 and an even larger rise occurred in 2009. Rising star rates rose from 6.45% in 2007 to 34.19% in 2009.

Figure 5.6 Historical Trends of Fallen Angel and Rising Star Rates for Cooperatives



5.2 Conditional Migration Matrix Analysis

This section investigates the potential dependencies that impact credit migration. The initial rating of the cooperative along with how it arrived at that rating was studied to offer insight on the likelihood of subsequent rating changes. The products and services offered by a cooperative are not homogeneous, and their functions may have an effect on rating stability. Therefore, the sample was conditioned on two cooperative types, grain marketing and farm supply/marketing. Time related conditions are examined since the performance of a cooperative most likely varies across different stages of the business cycle (Bangia et al., 2002; Nickell et al., 2000). The performance of the agricultural sector was also examined using Real Net Farm Income as a proxy as it is a measure of farm business profitability. Real Net Farm Income fluctuated and there were notable periods that had both favorable and unfavorable impacts on the performance of cooperatives.

5.2.1 Considering Prior Migration Experiences

First-order migration matrices do not consider experiences prior the current state. It is possible, however, that how a cooperative arrived at its current rating may have a bearing on its subsequent rating. That is, subsequent rating changes may be dependent on ratings history and not just time. The three types of ratings changes—upgraded, unchanged, and downgraded—were considered as the potential paths a cooperative could take in the previous one-year period prior to its change in the next period. Table 5.6 presents the migration behavior of cooperatives when the prior one-year period experience is considered with the standard errors in parentheses. Cooperatives that were previously unchanged were more likely to retain their rating (44.53%), while those previously upgraded were more likely to be downgraded (45.45%), and those previously downgraded had a higher likelihood of being upgraded (55.92%). The standard errors indicate the estimates of the upgraded to downgraded transition (1.78%) were the most variable followed by downgraded to downgraded transition (1.77%). The upgraded to upgraded transition (1.31%) had the smallest standard error. These results indicate that the prior rating experience impacts the direction of the path a cooperative follows.

Table 5.6 Subsequent Rating Changes Given Prior Experience

	Subsequent Behavior		
Prior Experience	Upgraded	Unchanged	Downgraded
Upgraded	15.88%	38.67%	45.45%
	(1.31%)	(1.74%)	(1.78%)
Unchanged	22.65%	44.53%	32.82%
	(1.38%)	(1.64%)	(1.55%)
Downgraded	55.92%	27.26%	16.82%
	(1.77%)	(1.59%)	(1.33%)

5.2.2 The Type of Cooperative

The dependence of the type of cooperative was studied by splitting the 1996–2013 sample into two sub-samples. One sub-sample was comprised of grain marketing cooperatives and the other sub-sample consisted of farm supply and marketing cooperatives. Two average migration matrices were then calculated (Table 5.7). All retention rates, except Aa and A, for farm supply and marketing cooperatives were higher than for grain marketing suggesting that they were more stable. In both types of cooperatives, retention rates did not strictly decline with decreasing credit quality. Farm supply and marketing cooperatives rated A were more likely to be downgraded (35.33%) than grain marketing cooperatives (19.61%). Farm supply and marketing cooperatives rated A were more likely to be downgraded than upgraded (24.01%) and grain marketing cooperatives rated A were more likely to be to be upgraded (35.29%) than downgraded. Investment rated grain marketing cooperatives were never downgraded to Caa, and

Aaa rated farm supply and marketing cooperatives were more stable (39.02%) than Aaa rated grain cooperatives (22.58%).

Table 5.7 Cooperative Type Conditional Matrices

Grain Marketing Cooperatives

	Terminal Rating						
Original Rating	Aaa	Aa	A	Baa	Ba	B	Caa
Aaa	22.58%	38.71%	32.26%	6.45%	0.00%	0.00%	0.00%
Aa	10.96%	52.05%	19.18%	10.27%	6.85%	0.68%	0.00%
A	4.90%	30.39%	45.10%	13.73%	4.90%	0.98%	0.00%
Baa	5.45%	25.45%	32.73%	21.82%	10.91%	3.64%	0.00%
Ba	0.00%	28.57%	7.14%	25.00%	21.43%	17.86%	0.00%
B	0.00%	36.36%	18.18%	18.18%	9.09%	9.09%	9.09%
Caa	0.00%	0.00%	0.00%	0.00%	0.00%	100.00%	0.00%

Farm Supply and Marketing Cooperatives

	Terminal Rating						
Original Rating	Aaa	Aa	A	Baa	Ba	B	Caa
Aaa	39.02%	37.80%	17.07%	4.88%	1.22%	0.00%	0.00%
Aa	6.46%	49.00%	24.50%	12.92%	5.12%	2.00%	0.00%
A	1.89%	22.13%	40.65%	24.70%	8.23%	1.89%	0.51%
Baa	1.13%	10.59%	28.17%	31.95%	19.66%	7.18%	1.32%
Ba	0.00%	6.41%	15.60%	28.69%	28.69%	16.71%	3.90%
B	0.00%	5.47%	12.44%	16.92%	25.87%	29.35%	9.95%
Caa	0.00%	1.72%	3.45%	10.34%	24.14%	34.48%	25.86%

5.2.3 The Business Cycle

To assess the impact of the state of the economy on the rating migration rates of cooperatives, the 1996–2013 sample was split into two sub-samples corresponding to observations that occurred during expansionary periods and those that occurred in recessionary periods as defined by the NBER. Two average migration matrices were then calculated (Table 5.8). During recessionary periods, retention rates for cooperatives rated A down through to B were more volatile. The difference in volatility was largest for B rated cooperatives (15.64%) followed by Ba rated cooperatives (11.87%). Cooperatives rated Aaa and Aa are similarly stable in both expansionary and recessionary periods. Aaa rated cooperatives were more likely to be downgraded below A during expansions (7.21%). Caa rated cooperatives had similar retention rates but more importantly indicated that they were more likely to transition to higher rating classes in both states of the economy. Overall, the probability of being downgraded was higher during expansions than in recessions for all ratings except Aaa. This was unusual since the expectation was for cooperatives to be consistently more likely to be downgraded during recessions across all rating classes.

Table 5.8 Business Cycle Conditional Transition Matrices

Expansions

	Terminal Rating						
Original Rating	Aaa	Aa	A	Baa	Ba	B	Caa
Aaa	34.78%	38.04%	19.57%	6.52%	1.09%	0.00%	0.00%
Aa	6.84%	49.70%	23.54%	12.27%	5.84%	1.81%	0.00%
A	2.23%	21.48%	42.27%	23.88%	7.90%	1.72%	0.52%
Baa	0.42%	10.21%	29.79%	31.04%	19.79%	7.71%	1.04%
Ba	0.00%	4.23%	14.33%	29.32%	30.62%	17.92%	3.58%
B	0.00%	4.17%	8.93%	19.64%	25.00%	31.55%	10.71%
Caa	0.00%	0.00%	2.27%	11.36%	22.73%	38.64%	25.00%

Recessions

	Terminal Rating						
Original Rating	Aaa	Aa	A	Baa	Ba	B	Caa
Aaa	33.33%	38.10%	28.57%	0.00%	0.00%	0.00%	0.00%
Aa	11.22%	50.00%	21.43%	12.24%	4.08%	1.02%	0.00%
A	2.91%	33.98%	35.92%	18.45%	6.80%	1.94%	0.00%
Baa	6.73%	20.19%	23.08%	30.77%	14.42%	2.88%	1.92%
Ba	0.00%	22.50%	17.50%	25.00%	18.75%	12.50%	3.75%
B	0.00%	18.18%	27.27%	6.82%	25.00%	15.91%	6.82%
Caa	0.00%	6.67%	6.67%	6.67%	26.67%	26.67%	26.67%

5.2.4 The Agricultural Sector

In addition to assessing migration behavior during expansionary and recessionary periods, the dependence of migration rates on the performance of the agricultural sector using RNFI, a measure of farm and farm business profitability was studied. Nickell et al. (2000) used tertiles of real GDP growth corresponding to different levels of economic activity to study the impact of the business cycle on bonds. Instead, this study used quartiles of RNFI (Table 5.9) to indicate the performance of the agricultural sector. The categories 'trough' and 'peak' corresponded to RNFI less than the first quartile and above the fourth quartile respectively whereas RNFI in-between the first and third quartile corresponded to 'normal times'. Three sub-samples corresponding to the three categories were then created followed by the calculation of three average migration matrices (Table 5.10). Figure 5.7 illustrates historical RNFI in 2019 US dollars. Profitability increased significantly from 2002 to 2004, slumped thereafter and trended upwards again from 2009 reaching $136 billion in 2013.

Figure 5.7 Historical Real Net Farm Income

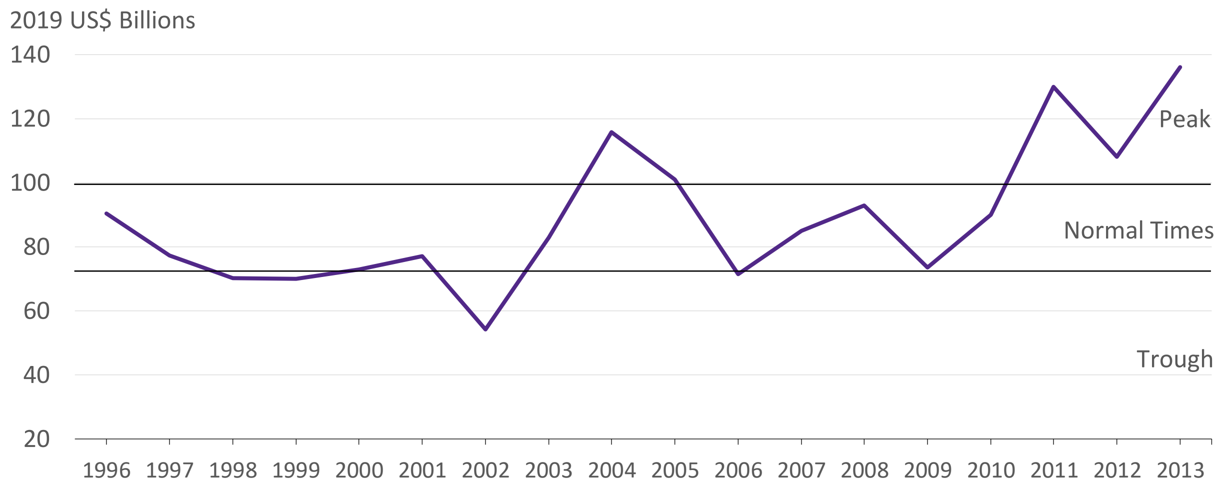


Table 5.9 Real Net Farm Income Quartiles, 2019 US$ Billions

Minimum	First Quartile	Median	Third Quartile	Maximum
54.20	73.01	83.90	99.05	136.10

The results of the matrices conditioned on RNFI were surprising. Cooperatives rated Aaa had a retention rate of 33.33% during peak periods, 38.18% during normal times, and 30.00% during trough periods. These results indicated that Aaa rated cooperatives were less stable in peak times than in normal times. Although, cooperatives rated investment grade were more stable during peak periods except for those rated Aaa, non-investment grade cooperatives were most stable during troughs. Migration rates in peak times presented further surprises. Cooperatives rated Aaa were more likely to be downgraded to Aa rather than retain their original ratings. Furthermore, these findings contradicted the expectation of observing the highest probabilities along the diagonal of the matrix. In most instances, cooperatives were more likely to be upgraded during peak times and more likely to be downgraded during normal times and troughs.

Table 5.10 Transition Matrices Conditional on Real Net Farm Income

	Peak						
	Terminal Rating						
Original Rating	Aaa	Aa	A	Baa	Ba	B	Caa
Aaa	33.33%	44.44%	16.67%	5.56%	0.00%	0.00%	0.00%
Aa	5.84%	57.79%	22.73%	9.74%	3.25%	0.65%	0.00%
A	0.60%	25.75%	47.31%	19.76%	4.79%	1.80%	0.00%
Baa	0.00%	10.96%	34.25%	34.93%	13.01%	6.85%	0.00%
Ba	0.00%	9.52%	22.62%	26.19%	29.76%	9.52%	2.38%
B	0.00%	2.17%	8.70%	19.57%	34.78%	26.09%	8.70%
Caa	0.00%	0.00%	0.00%	0.00%	0.00%	80.00%	20.00%
	Normal Times						
	Terminal Rating						
Original Rating	Aaa	Aa	A	Baa	Ba	B	Caa
Aaa	38.18%	30.91%	23.64%	7.27%	0.00%	0.00%	0.00%
Aa	8.50%	51.02%	20.75%	11.56%	6.80%	1.36%	0.00%
A	4.03%	25.50%	38.59%	22.82%	7.05%	2.01%	0.00%
Baa	3.46%	14.23%	26.92%	29.23%	19.62%	5.00%	1.54%
Ba	0.00%	11.54%	15.93%	30.22%	24.18%	15.93%	2.20%
B	0.00%	11.02%	16.10%	18.64%	22.03%	24.58%	7.63%
Caa	0.00%	3.03%	6.06%	6.06%	33.33%	30.30%	21.21%
	Trough						
	Terminal Rating						
Original Rating	Aaa	Aa	A	Baa	Ba	B	Caa
Aaa	30.00%	45.00%	20.00%	2.50%	2.50%	0.00%	0.00%
Aa	7.48%	38.78%	28.57%	16.33%	5.44%	3.40%	0.00%
A	1.36%	18.64%	40.45%	25.91%	10.91%	1.36%	1.36%
Baa	0.00%	9.55%	26.40%	30.34%	22.47%	9.55%	1.69%

Ba	0.00%	1.65%	8.26%	27.27%	33.06%	23.14%	6.61%
B	0.00%	2.08%	8.33%	10.42%	22.92%	39.58%	16.67%
Caa	0.00%	0.00%	0.00%	19.05%	14.29%	33.33%	33.33%

5.3 Comparing the Precision of the Estimated Probabilities

Since diagonal elements mostly had the largest frequencies in all the samples, retention rate estimates are likely the most reliable statistics in this study. Table 5.11 shows the coefficient of variation (CV) of retention rates corresponding to their respective samples. CV measures the variability of an estimate relative to its mean. Estimates obtained from farm supply and marketing cooperatives had smaller variations relative to their means across all ratings compared to grain marketing cooperatives while retention rates estimated from observations during expansions had lower CVs across all ratings compared to those estimated during recessions. Aaa, Aa, A, Baa, and B retention rates estimated during normal times had the smallest variation when compared to retention rates estimated during peak and trough times. Excluding Caa rated cooperatives, retention rates estimated from the unconditional sample had the smallest CVs compared to all other samples.

Table 5.11 Coefficients of Variation of Sample Retention Rates

Sample	Aaa	Aa	A	Baa	Ba	B	Caa
Unconditional	12.96%	4.12%	4.55%	6.17%	8.12%	10.93%	22.30%
Grain Marketing	33.26%	7.94%	10.92%	25.52%	36.19%	95.35%	0.00%
Farm Supply and Marketing	13.80%	4.81%	5.00%	6.35%	8.32%	10.94%	22.23%
Expansions	14.28%	4.51%	4.84%	6.80%	8.59%	11.36%	26.11%
Recessions	30.86%	10.10%	13.16%	14.71%	23.27%	34.66%	42.82%
Peak	33.33%	6.89%	8.17%	11.30%	16.76%	24.82%	89.44%
Normal Times	17.16%	5.71%	7.31%	9.65%	13.13%	16.13%	33.55%
Trough	24.15%	10.36%	8.18%	11.36%	12.94%	17.83%	30.86%

5.4 The Predictive Ability of the Unconditional Transition Matrix

Table 5.12 shows the deviation of the observed 2013–2014 one-year migration matrix from the unconditional migration matrix estimated from the 1996–2013 sample. Each element of the matrix is the difference between their corresponding values in the observed migration matrix and the unconditional migration matrix. A negative deviation indicates the unconditional matrix over-estimated the observed transition probability and a positive deviation indicates the unconditional matrix under-estimated the observed transition probability. Upgrading to B from Caa is the most over-estimated transition (-35.59%) while upgrading to Baa from B is the most under-estimated transition (33.02%). Retaining A (-1.31%) was well predicted by the unconditional one-year migration matrix. Most predicted retentions rates had large differences than what was actually observed. The frequent large cell-by-cell deviations indicate that the unconditional one-year migration matrix performed poorly in predicting the observed 2013–2014 transitions.

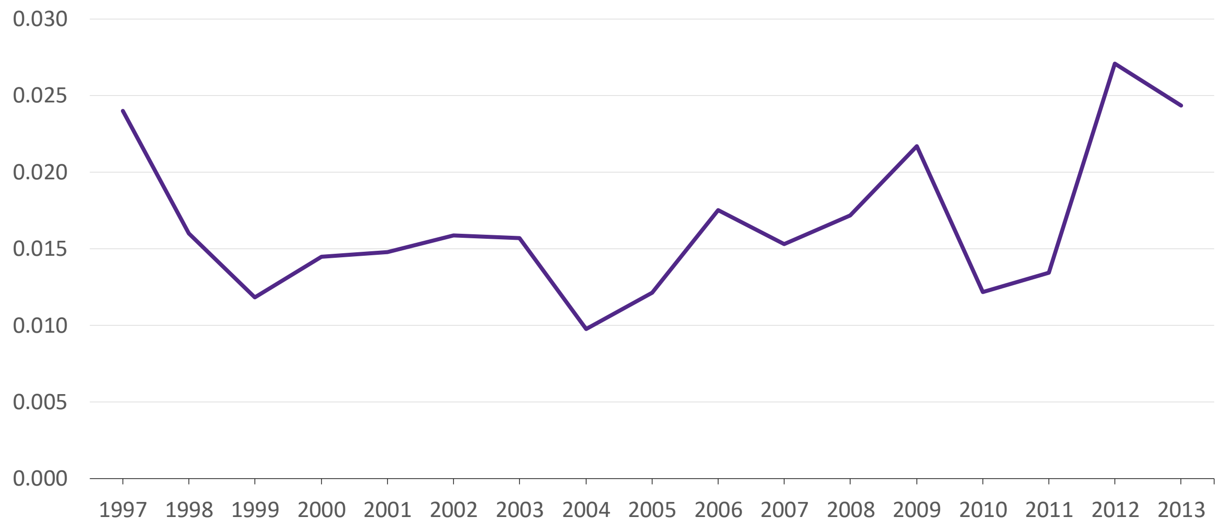
Table 5.12 Deviation from the Unconditional Migration Matrix

	Terminal Rating						
Original Rating	Aaa	Aa	A	Baa	Ba	B	Caa
Aaa	-34.51%	11.95%	28.76%	-5.31%	-0.88%	0.00%	0.00%
Aa	-0.78%	19.74%	-1.16%	-10.57%	-5.55%	-1.68%	0.00%
A	-0.52%	-6.99%	-1.31%	6.03%	3.17%	0.07%	-0.44%
Baa	-1.54%	-2.90%	-19.50%	23.55%	-0.65%	2.24%	-1.20%
Ba	0.00%	3.10%	-14.99%	4.91%	16.28%	-5.68%	-3.62%
B	0.00%	-7.08%	-12.74%	33.02%	0.00%	-3.30%	-9.91%
Caa	0.00%	-1.69%	-3.39%	-10.17%	26.27%	-35.59%	24.58%

5.5 Detecting Time-Inhomogeneity

The L^2 Norm is used to detect changes in regimes across periods. Figure 5.8 shows the L^2 Norms calculated by comparing the element distance of every annual one-year migration matrices with the unconditional migration matrix estimated from the entire 1996–2013 sample. The year 2004 was the most similar period to the unconditional migration matrix while 2012 had the largest difference in transition probabilities. The L^2 Norm was not close to zero nor was it horizontal. The annual variation of the L^2 Norm indicates that there were changes in regimes from period to period.

Figure 5.8 The L2 Norm, Annual One-Year Matrices vs. One-Year Average Matrix



5.6 Testing for Time-Dependence

The study assumed the rating transitions were Markovian and first-order. Time-dependence was tested using the Likelihood Ratio (LR) and Pearson χ^2 (Q) tests. The LR and Q tests were twofold. The stochastic process was first tested to confirm that it was not a zero-order process. Then, the process was tested to confirm that it was a first-order stochastic process. The order was assumed to be inconclusive if the first-order test was rejected.

5.6.1 The Unconditional Case

The test comparing the zero-order against the first order Markov Property is rejected by both the LR = 595.2, and Q = 1444 with 36 degrees of freedom at the 5% statistical significance level. The test was repeated comparing the first-order against the second order Markov chain. Again, the null comparing the first-order chain with the second-order was rejected at the 5% statistical significance level using both test statistics. LR and Q were 373.58 and 390.20 respectively with 252 degrees of freedom. Therefore, the order for the unconditional case was inconclusive. This means the unconditional matrix cannot be used to predict future distributions of cooperatives ratings since the process cannot be confirmed to be a first-order Markov chain.

5.6.2 The Type of Cooperative

The zero-order assumption was rejected for grain cooperatives, with Q of 158.32 with 36 degrees of freedom at the 5% statistical significance level. However, the null hypothesis, using LR = 49.13 with 36 degrees of freedom, was not rejected at the same level of significance. Therefore, the order of the rating dependency of grain marketing cooperatives was a zero.

The null hypothesis for the zero-order assumption for farm supply and marketing cooperatives was rejected by both test statistics. LR = 525.64 and Q = 1328.89 with 36 degrees of freedom. The first-order assumption was also rejected at the same significance level. Test statistics were LR = 348.82 and Q = 385.67 with 252 degrees of freedom. Therefore, the degree of dependency was inconclusive.

5.6.3 The Stage in the Business Cycle

The zero-order assumption test statistics for the expansion sub-sample were LR = 545.87 and Q = 1316.63 with 36 degrees of freedom. The null was rejected at a statistical significance level of 5%. The first-order assumption resulted in LR = 350.51 and Q = 366.26 with 252 degrees of freedom. The null hypothesis was also rejected using both tests statistics at the same significance level. Therefore, the order of the stochastic process during expansions was inconclusive.

Test statistics assessing the zero-order assumption for recessions were LR = 86.36 and Q = 194.02 with 36 degrees of freedom. The first-order assumption was rejected at the 5% level of statistical significance. There were not enough periods to test the first-order assumption, and thus the recessionary stochastic process was inconclusive.

5.6.4 The Stage of the Agricultural Business Cycle

The zero-order test for peak periods resulted in test statistics of LR = 166.97 and Q = 431.12 with 36 degrees of freedom. The null hypothesis was rejected using both test statistics at the 5% statistical significance level. There were not enough periods to test the first-order Markov property and as a result the degree of dependency was inconclusive.

The zero-order assumption was again rejected at the 5% significance level during normal times. The test statistics were LR = 257.66 and Q = 611.40 with 36 degrees of freedom. There were not enough observations to test the first-order Markov property therefore the order of dependency is inconclusive.

Test statistics for the zero-order test during troughs were LR = 213.99 and Q = 490.77 with 36 degrees of freedom. The null was rejected by both test statistics at the 5% statistical significance level. Similar to the peak and normal times sub-samples, there were not enough observations to construct a second-order Markov chain and test the first order property. Therefore, the degree of dependency was inconclusive.

Grain marketing cooperatives were the only sub-sample that resulted in the order of the process being determined. Therefore, stationarity is tested for this sub-sample only.

5.7 Testing for Time-Homogeneity

There was evidence of regime change in the sample as observed by the detection of time-inhomogeneity by the L^2 Norms. The grain marketing sub-sample was split into two similarly sized sub-periods to test for time-homogeneity using the Likelihood Ratio (LR) and Pearson χ^2 (Q) tests. It is possible for the test results to differ. According to Bickenbach and Bode (2003), the Pearson statistic is sensitive to very low transition probabilities estimated from the entire sample, and as a result, it is more reasonable to infer conclusions of time-homogeneity based on the LR.

The grain sub-sample was split into two sub-periods. Sub-period 1 spanned from 1996–2005, and sub-period 2 spanned from 2005-2013. Time-homogeneity failed to be rejected using the Q = 33.65 test statistic with 22 degrees of freedom at the $\alpha = 0.05$ significance level. The p-value was 0.0533. However, the null hypothesis was rejected using the LR = 39.93 test statistic with 22 degrees of freedom. Therefore, the conclusion is that the transition probabilities of grain cooperatives were non-time-homogeneous, and the order of the rating process was inconclusive.

5.8 Discussion

The average cooperative in the 1996–2013 sample had a prime rating of Baa. Of the 2,790 cooperative observations, 75.89% were rated prime, and 24.12% were rated not prime. When the letter grade was considered, only 117 (4.19%) were rated Aaa, the highest possible rating, and 61 (2.19%) were rated Caa, the lowest possible rating. Most sample years experienced a negative rating drift implying downgrades exceeded upgrades. The large spike in upgrades during the 2008–2009 period was a result of the runup in grain prices that contributed to improved profitability. Retention rates were much smaller than the estimates calculated by Altman and Kao (1992b), Nickell et al. (2000), Bangia et al. (2002), and Carty (1997). The smaller retention rates resulted in the probabilities around the diagonal of the matrix being larger than those estimated in the aforementioned studies. The observed higher volatility of cooperatives may confirm the stabilizing effects of subjective components outlined by Gloy et al.

(2005). The rating stability does not deteriorate strictly with decreasing credit quality since, in the unconditional case, Aa rated cooperatives were more stable than those rated Aaa and B rated cooperatives were slightly more stable than those rate Ba. In the long-run, the steady state indicated that cooperatives were most likely to transition to the A rating and were unlikely to be downgraded or remain rated Caa.

Although most retention rates declined with increasing time horizon they did not do so continuously as observed by Altman and Kao (1992b). The proportion unchanged showed a declining trend for the first 12 years and subsequently trended upwards thereafter. Cooperatives were more likely to transition than remain unchanged. When the direction of the rating change was considered, cooperatives were more likely to be upgraded than downgraded albeit with a similar probability. Rising star rates exhibited a moderate negative relationship, implied by the correlation coefficient, with the Effective Federal Funds Rate. This suggested a propensity for upgrades as funding costs declined. The opposite relationship was not observed with rising star rates nor was there any meaningful relationship with changes in RNFI.

Path dependence in the migration process was identified when prior migration experiences were considered. The results confirmed that the prior credit rating history had predictive power of the subsequent rating's direction. Relative to the conditional migration matrices, the unconditional migration matrix had the most reliable estimates, as measured by the coefficient of variation. The lower variation of the unconditional matrix was primarily attributed to a larger frequency of possible rating transitions. Grain marketing cooperatives had a higher likelihood of being upgraded than farm supply/marketing. The stability of cooperatives conditioned on the business cycle were similar however differed by propensity to upgrade or downgrade. It was surprising that Aaa cooperatives were more likely to be downgraded to Aa during peak agricultural periods instead of retaining their rating. The expectation was for cooperatives to improve in stability in more favorable conditions. Nevertheless, cooperatives were generally more likely to be upgraded during peak times and more likely to be downgraded in normal times and troughs in most instances.

The variance in relative values of the L^2 Norm indicated the presence of multiple regimes in the sample and provided further evidence that the estimated probabilities were likely non-stationary. Although grain cooperatives were found to be zero-order, stationarity across time was not confirmed. The results of the statistical tests concluded that the rating process is not a first-order Markov chain. The implication of not knowing the order of the process is that the number of prior periods that determine the rating path a cooperative would take cannot be determined. Consequently, the steady state distribution calculated may not provide accurate predictions of rating transitions in the long-run.

Chapter 6 - Conclusion & Recommendations

The purpose of this study was to assess the credit rating migration behavior of the risk of agricultural cooperatives. The Credit Metrics component of Moody's Global Agricultural Cooperatives Industry Rating Methodology was used to assign annual credit ratings. The Credit Metrics component was used to solely assess a cooperative's financial risk. An unconditional matrix and matrices conditioned on the type of cooperative, stage of the business cycle, and the performance of the agriculture sector were estimated. Matrices that varied by time horizon were also estimated. Rating drift and rating activity were calculated to assess the trends in credit quality across the sample in addition to rating magnitude. Coefficients of variation and standard errors of the estimates were calculated to measure precision and reliability. The L^2 Norm was used to detect regime change and the Pearson χ^2 and the Likelihood Ratio test were used to test the assumptions of time-homogeneity and the Markov property.

Stability of cooperatives generally declined with increasing time horizon but did not do so strictly. Most sample years experienced a negative rating drift implying downgrades exceeded upgrades. Cooperatives were more likely to experience a credit rating transition than remain unchanged. The average size of the notch change was 0.46. Moreover, cooperatives were more likely to experience a downgrade than an upgrade and the average downgrade notch size (0.47) was slightly larger than the average upgrade notch size (0.45). There were numerous instances of downgrades and upgrades spanning across multiple rating classes. Because cooperatives being small and not diversified enough to withstand adverse challenges to their operations, notch size is high. The results confirmed that the prior credit rating history had predictive power of the subsequent rating's direction. Multiple regimes in the sample were detected and migration probabilities of grain marketing cooperatives to be non-stationary. The rating process did not follow a first order Markov chain.

The findings of this study provide agricultural cooperative lenders, managers, and directors with a comprehensive information set of how credit risk changes from period to period. A useful application would be the self-assessment of a cooperative against the performance of its peers. For example, a strategy’s effectiveness over time can be assessed; that is, has the credit risk of a cooperative improved or deteriorated under the strategy? In addition, the impact of a change of strategy on credit risk can be assessed.

The contribution to the literature is a first attempt in the assessment of the historical behavior of changes in credit risk of cooperatives. It conceptualizes the expected credit risk behavior of cooperatives over time and responses to exogenous favorable and adverse factors. A limitation of this study is that a discrete-time Markov chain was used to obtain transition probabilities. A one-year migration matrix is unable to capture all the changes in credit risk that occur over an annual interval. Future research would include assessing the migration behavior of cooperatives using lenders’ internal ratings in continuous-time instead of discrete-time. Internal ratings would capture subjective and objective components from the lender’s perspective. To improve the accuracy of the estimates, a larger dataset consisting of more cooperatives and sample years would be beneficial.

Chapter 7 - References

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Appendix A - Additional Tables & Figures

Table A.1 Retention Rates by Credit Rating as Time Horizon Increases

Time Horizon	Aaa	Aa	A	Baa	Ba	B	Caa
1	62.50%	68.42%	34.15%	22.22%	21.74%	25.00%	0.00%
2	37.50%	47.37%	43.90%	13.89%	13.04%	37.50%	0.00%
3	12.50%	39.47%	26.83%	25.00%	21.74%	37.50%	0.00%
4	25.00%	36.84%	36.59%	22.22%	26.09%	12.50%	100.00%
5	12.50%	34.21%	29.27%	30.56%	26.09%	25.00%	0.00%
6	37.50%	21.05%	24.39%	25.00%	26.09%	12.50%	0.00%
7	0.00%	36.84%	26.83%	19.44%	8.70%	37.50%	100.00%
8	37.50%	39.47%	21.95%	25.00%	17.39%	25.00%	0.00%
9	12.50%	31.58%	34.15%	25.00%	17.39%	12.50%	0.00%
10	0.00%	18.42%	34.15%	27.78%	30.43%	0.00%	0.00%
11	12.50%	18.42%	24.39%	27.78%	26.09%	25.00%	0.00%
12	0.00%	5.26%	19.51%	30.56%	34.78%	37.50%	0.00%
13	62.50%	50.00%	29.27%	11.11%	8.70%	12.50%	100.00%
14	25.00%	47.37%	36.59%	25.00%	8.70%	12.50%	100.00%
15	0.00%	36.84%	29.27%	25.00%	21.74%	12.50%	0.00%
16	12.50%	50.00%	34.15%	30.56%	8.70%	12.50%	0.00%
17	0.00%	50.00%	41.46%	8.33%	8.70%	12.50%	0.00%
Average	**20.59%**	**37.15%**	**30.99%**	**23.20%**	**19.18%**	**20.59%**	**23.53%**

Table A.2 Migration Rate Behavior, One to Five-Year Time Horizon

Migration Rates 1 Year Later

	Aaa	Aa	A	Baa	Ba	B	Caa
Aaa	34.51%	38.05%	21.24%	5.31%	0.88%	0.00%	0.00%
Aa	7.56%	49.75%	23.19%	12.27%	5.55%	1.68%	0.00%
A	2.34%	23.36%	41.31%	23.07%	7.74%	1.75%	0.44%
Baa	1.54%	11.99%	28.60%	30.99%	18.84%	6.85%	1.20%
Ba	0.00%	8.01%	14.99%	28.42%	28.17%	16.80%	3.62%
B	0.00%	7.08%	12.74%	16.98%	25.00%	28.30%	9.91%
Caa	0.00%	1.69%	3.39%	10.17%	23.73%	35.59%	25.42%

Migration Rates 2 Years Later

	Aaa	Aa	A	Baa	Ba	B	Caa
Aaa	26.79%	33.93%	25.00%	12.50%	1.79%	0.00%	0.00%
Aa	7.50%	40.77%	26.14%	16.45%	7.31%	1.65%	0.18%
A	2.66%	23.35%	36.99%	22.10%	10.97%	3.13%	0.78%
Baa	1.65%	18.46%	24.68%	28.52%	18.83%	6.58%	1.28%
Ba	0.00%	8.31%	21.18%	27.08%	21.18%	17.16%	5.09%
B	0.49%	9.80%	15.20%	14.71%	26.47%	25.98%	7.35%
Caa	0.00%	3.39%	8.47%	11.86%	18.64%	38.98%	18.64%

Migration Rates 3 Years Later

	Aaa	Aa	A	Baa	Ba	B	Caa
Aaa	23.42%	42.34%	24.32%	9.01%	0.90%	0.00%	0.00%
Aa	6.82%	38.79%	27.10%	16.76%	7.60%	2.14%	0.78%
A	2.50%	23.50%	33.50%	23.00%	12.67%	3.83%	1.00%
Baa	1.18%	17.32%	25.20%	29.72%	17.13%	7.48%	1.97%
Ba	0.58%	9.86%	21.16%	28.70%	20.87%	14.78%	4.06%
B	0.00%	7.33%	16.75%	13.09%	27.75%	29.84%	5.24%
Caa	0.00%	7.02%	5.26%	12.28%	24.56%	29.82%	21.05%

Migration Rates 4 Years Later

	Aaa	Aa	A	Baa	Ba	B	Caa
Aaa	18.27%	40.38%	28.85%	7.69%	2.88%	1.92%	0.00%
Aa	6.13%	38.29%	25.60%	16.85%	9.41%	2.41%	1.31%
A	3.21%	26.07%	33.21%	20.89%	10.71%	5.00%	0.89%
Baa	1.66%	16.15%	26.50%	26.50%	18.01%	9.32%	1.86%
Ba	0.61%	10.61%	20.00%	28.48%	23.94%	13.64%	2.73%
B	0.00%	10.50%	13.81%	24.31%	19.89%	23.76%	7.73%
Caa	0.00%	1.82%	10.91%	18.18%	25.45%	27.27%	16.36%

Migration Rates 5 Years Later

	Aaa	Aa	A	Baa	Ba	B	Caa
Aaa	23.60%	40.45%	25.84%	4.49%	3.37%	2.25%	0.00%
Aa	6.72%	36.32%	26.62%	15.92%	8.46%	4.23%	1.74%
A	2.89%	26.97%	31.41%	19.85%	10.79%	6.36%	1.73%
Baa	0.86%	19.87%	24.62%	29.16%	16.85%	6.70%	1.94%
Ba	0.63%	11.32%	22.33%	25.79%	25.16%	13.21%	1.57%
B	0.57%	9.77%	14.94%	24.14%	20.69%	24.14%	5.75%
Caa	0.00%	8.00%	16.00%	18.00%	16.00%	30.00%	12.00%

Table A.3 One-Year Average Rating Transition Matrix, Farm Supply and Marketing

	Aaa	Aa	A	Baa	Ba	B	Caa
Aaa	39.02%	37.80%	17.07%	4.88%	1.22%	0.00%	0.00%
	(5.4)	(5.4)	(4.2)	(2.4)	(1.2)	(0.0)	(0.0)
Aa	6.46%	49.00%	24.50%	12.92%	5.12%	2.00%	0.00%
	(1.2)	(2.4)	(2.0)	(1.6)	(1.0)	(0.7)	(0.0)
A	1.89%	22.13%	40.65%	24.70%	8.23%	1.89%	0.51%
	(0.6)	(1.7)	(2.0)	(1.8)	(1.1)	(0.6)	(0.3)
Baa	1.13%	10.59%	28.17%	31.95%	19.66%	7.18%	1.32%
	(0.5)	(1.3)	(2.0)	(2.0)	(1.7)	(1.1)	(0.5)
Ba	0.00%	6.41%	15.60%	28.69%	28.69%	16.71%	3.90%
	(0.0)	(1.3)	(1.9)	(2.4)	(2.4)	(2.0)	(1.0)
B	0.00%	5.47%	12.44%	16.92%	25.87%	29.35%	9.95%
	(0.0)	(1.6)	(2.3)	(2.6)	(3.1)	(3.2)	(2.1)
Caa	0.00%	1.72%	3.45%	10.34%	24.14%	34.48%	25.86%
	(0.0)	(1.7)	(2.4)	(4.0)	(5.6)	(6.2)	(5.7)

Table A.4 One-Year Average Rating Transition Matrix, Grain Marketing

	Aaa	Aa	A	Baa	Ba	B	Caa
Aaa	22.58%	38.71%	32.26%	6.45%	0.00%	0.00%	0.00%
	(7.5)	(8.7)	(8.4)	(4.4)	(0.0)	(0.0)	(0.0)
Aa	10.96%	52.05%	19.18%	10.27%	6.85%	0.68%	0.00%
	(2.6)	(4.1)	(3.3)	(2.5)	(2.1)	(0.7)	(0.0)
A	4.90%	30.39%	45.10%	13.73%	4.90%	0.98%	0.00%
	(2.1)	(4.6)	(4.9)	(3.4)	(2.1)	(1.0)	(0.0)
Baa	5.45%	25.45%	32.73%	21.82%	10.91%	3.64%	0.00%
	(3.1)	(5.9)	(6.3)	(5.6)	(4.2)	(2.5)	(0.0)
Ba	0.00%	28.57%	7.14%	25.00%	21.43%	17.86%	0.00%
	(0.0)	(8.5)	(4.9)	(8.2)	(7.8)	(7.2)	(0.0)
B	0.00%	36.36%	18.18%	18.18%	9.09%	9.09%	9.09%
	(0.0)	(14.5)	(11.6)	(11.6)	(8.7)	(8.7)	(8.7)
Caa	0.00%	0.00%	0.00%	0.00%	0.00%	100.00%	0.00%
	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)

Table A.5 One-Year Average Rating Transition Matrix, Expansionary Periods

	Aaa	Aa	A	Baa	Ba	B	Caa
Aaa	34.78%	38.04%	19.57%	6.52%	1.09%	0.00%	0.00%
	(5.0)	(5.1)	(4.1)	(2.6)	(1.1)	(0.0)	(0.0)
Aa	6.84%	49.70%	23.54%	12.27%	5.84%	1.81%	0.00%
	(1.1)	(2.2)	(1.9)	(1.5)	(1.1)	(0.6)	(0.0)
A	2.23%	21.48%	42.27%	23.88%	7.90%	1.72%	0.52%
	(0.6)	(1.7)	(2.0)	(1.8)	(1.1)	(0.5)	(0.3)
Baa	0.42%	10.21%	29.79%	31.04%	19.79%	7.71%	1.04%
	(0.3)	(1.4)	(2.1)	(2.1)	(1.8)	(1.2)	(0.5)
Ba	0.00%	4.23%	14.33%	29.32%	30.62%	17.92%	3.58%
	(0.0)	(1.1)	(2.0)	(2.6)	(2.6)	(2.2)	(1.1)
B	0.00%	4.17%	8.93%	19.64%	25.00%	31.55%	10.71%
	(0.0)	(1.5)	(2.2)	(3.1)	(3.3)	(3.6)	(2.4)
Caa	0.00%	0.00%	2.27%	11.36%	22.73%	38.64%	25.00%
	(0.0)	(0.0)	(2.2)	(4.8)	(6.3)	(7.3)	(6.5)

Table A.6 One-Year Average Rating Transition Matrix, Recessionary Periods

	Aaa	Aa	A	Baa	Ba	B	Caa
Aaa	33.33%	38.10%	28.57%	0.00%	0.00%	0.00%	0.00%
	(10.3)	(10.6)	(9.9)	(0.0)	(0.0)	(0.0)	(0.0)
Aa	11.22%	50.00%	21.43%	12.24%	4.08%	1.02%	0.00%
	(3.2)	(5.1)	(4.1)	(3.3)	(2.0)	(1.0)	(0.0)
A	2.91%	33.98%	35.92%	18.45%	6.80%	1.94%	0.00%
	(1.7)	(4.7)	(4.7)	(3.8)	(2.5)	(1.4)	(0.0)
Baa	6.73%	20.19%	23.08%	30.77%	14.42%	2.88%	1.92%
	(2.5)	(3.9)	(4.1)	(4.5)	(3.4)	(1.6)	(1.3)
Ba	0.00%	22.50%	17.50%	25.00%	18.75%	12.50%	3.75%
	(0.0)	(4.7)	(4.2)	(4.8)	(4.4)	(3.7)	(2.1)
B	0.00%	18.18%	27.27%	6.82%	25.00%	15.91%	6.82%
	(0.0)	(5.8)	(6.7)	(3.8)	(6.5)	(5.5)	(3.8)
Caa	0.00%	6.67%	6.67%	6.67%	26.67%	26.67%	26.67%
	(0.0)	(6.4)	(6.4)	(6.4)	(11.4)	(11.4)	(11.4)

Table A.7 One-Year Average Rating Transition Matrix, Peak

	Aaa	Aa	A	Baa	Ba	B	Caa
Aaa	33.33%	44.44%	16.67%	5.56%	0.00%	0.00%	0.00%
	(11.1)	(11.7)	(8.8)	(5.4)	(0.0)	(0.0)	(0.0)
Aa	5.84%	57.79%	22.73%	9.74%	3.25%	0.65%	0.00%
	(1.9)	(4.0)	(3.4)	(2.4)	(1.4)	(0.6)	(0.0)
A	0.60%	25.75%	47.31%	19.76%	4.79%	1.80%	0.00%
	(0.6)	(3.4)	(3.9)	(3.1)	(1.7)	(1.0)	(0.0)
Baa	0.00%	10.96%	34.25%	34.93%	13.01%	6.85%	0.00%
	(0.0)	(2.6)	(3.9)	(3.9)	(2.8)	(2.1)	(0.0)
Ba	0.00%	9.52%	22.62%	26.19%	29.76%	9.52%	2.38%
	(0.0)	(3.2)	(4.6)	(4.8)	(5.0)	(3.2)	(1.7)
B	0.00%	2.17%	8.70%	19.57%	34.78%	26.09%	8.70%
	(0.0)	(2.2)	(4.2)	(5.8)	(7.0)	(6.5)	(4.2)
Caa	0.00%	0.00%	0.00%	0.00%	0.00%	80.00%	20.00%
	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(17.9)	(17.9)

Table A.8 One-Year Average Rating Transition Matrix, Normal Times

	Aaa	Aa	A	Baa	Ba	B	Caa
Aaa	38.18%	30.91%	23.64%	7.27%	0.00%	0.00%	0.00%
	(6.6)	(6.2)	(5.7)	(3.5)	(0.0)	(0.0)	(0.0)
Aa	8.50%	51.02%	20.75%	11.56%	6.80%	1.36%	0.00%
	(1.6)	(2.9)	(2.4)	(1.9)	(1.5)	(0.7)	(0.0)
A	4.03%	25.50%	38.59%	22.82%	7.05%	2.01%	0.00%
	(1.1)	(2.5)	(2.8)	(2.4)	(1.5)	(0.8)	(0.0)
Baa	3.46%	14.23%	26.92%	29.23%	19.62%	5.00%	1.54%
	(1.1)	(2.2)	(2.8)	(2.8)	(2.5)	(1.4)	(0.8)
Ba	0.00%	11.54%	15.93%	30.22%	24.18%	15.93%	2.20%
	(0.0)	(2.4)	(2.7)	(3.4)	(3.2)	(2.7)	(1.1)
B	0.00%	11.02%	16.10%	18.64%	22.03%	24.58%	7.63%
	(0.0)	(2.9)	(3.4)	(3.6)	(3.8)	(4.0)	(2.4)
Caa	0.00%	3.03%	6.06%	6.06%	33.33%	30.30%	21.21%
	(0.0)	(3.0)	(4.2)	(4.2)	(8.2)	(8.0)	(7.1)

Table A.9 One-Year Average Rating Transition Matrix, Trough

	Aaa	Aa	A	Baa	Ba	B	Caa
Aaa	30.00%	45.00%	20.00%	2.50%	2.50%	0.00%	0.00%
	(7.2)	(7.9)	(6.3)	(2.5)	(2.5)	(0.0)	(0.0)
Aa	7.48%	38.78%	28.57%	16.33%	5.44%	3.40%	0.00%
	(2.2)	(4.0)	(3.7)	(3.0)	(1.9)	(1.5)	(0.0)
A	1.36%	18.64%	40.45%	25.91%	10.91%	1.36%	1.36%
	(0.8)	(2.6)	(3.3)	(3.0)	(2.1)	(0.8)	(0.8)
Baa	0.00%	9.55%	26.40%	30.34%	22.47%	9.55%	1.69%
	(0.0)	(2.2)	(3.3)	(3.4)	(3.1)	(2.2)	(1.0)
Ba	0.00%	1.65%	8.26%	27.27%	33.06%	23.14%	6.61%
	(0.0)	(1.2)	(2.5)	(4.0)	(4.3)	(3.8)	(2.3)
B	0.00%	2.08%	8.33%	10.42%	22.92%	39.58%	16.67%
	(0.0)	(2.1)	(4.0)	(4.4)	(6.1)	(7.1)	(5.4)
Caa	0.00%	0.00%	0.00%	19.05%	14.29%	33.33%	33.33%
	(0.0)	(0.0)	(0.0)	(8.6)	(7.6)	(10.3)	(10.3)

Table A.10 Two-Year Average Rating Transition Matrix, 1996–2013

	Terminal Rating						
Original Rating	Aaa	Aa	A	Baa	Ba	B	Caa
Aaa	26.79%	33.93%	25.00%	12.50%	1.79%	0.00%	0.00%
	(4.2)	(4.5)	(4.1)	(3.1)	(1.3)	(0.0)	(0.0)
Aa	7.50%	40.77%	26.14%	16.45%	7.31%	1.65%	0.18%
	(1.1)	(2.1)	(1.9)	(1.6)	(1.1)	(0.5)	(0.2)
A	2.66%	23.35%	36.99%	22.10%	10.97%	3.13%	0.78%
	(0.6)	(1.7)	(1.9)	(1.6)	(1.2)	(0.7)	(0.3)
Baa	1.65%	18.46%	24.68%	28.52%	18.83%	6.58%	1.28%
	(0.5)	(1.7)	(1.8)	(1.9)	(1.7)	(1.1)	(0.5)
Ba	0.00%	8.31%	21.18%	27.08%	21.18%	17.16%	5.09%
	(0.0)	(1.4)	(2.1)	(2.3)	(2.1)	(2.0)	(1.1)
B	0.49%	9.80%	15.20%	14.71%	26.47%	25.98%	7.35%
	(0.5)	(2.1)	(2.5)	(2.5)	(3.1)	(3.1)	(1.8)
Caa	0.00%	3.39%	8.47%	11.86%	18.64%	38.98%	18.64%
	(0.0)	(2.4)	(3.6)	(4.2)	(5.1)	(6.3)	(5.1)

Table A.11 Three-Year Average Rating Transition Matrix, 1996–2013

	Terminal Rating						
Original Rating	Aaa	Aa	A	Baa	Ba	B	Caa
Aaa	23.42%	42.34%	24.32%	9.01%	0.90%	0.00%	0.00%
	(4.0)	(4.7)	(4.1)	(2.7)	(0.9)	(0.0)	(0.0)
Aa	6.82%	38.79%	27.10%	16.76%	7.60%	2.14%	0.78%
	(1.1)	(2.2)	(2.0)	(1.6)	(1.2)	(0.6)	(0.4)
A	2.50%	23.50%	33.50%	23.00%	12.67%	3.83%	1.00%
	(0.6)	(1.7)	(1.9)	(1.7)	(1.4)	(0.8)	(0.4)
Baa	1.18%	17.32%	25.20%	29.72%	17.13%	7.48%	1.97%
	(0.5)	(1.7)	(1.9)	(2.0)	(1.7)	(1.2)	(0.6)
Ba	0.58%	9.86%	21.16%	28.70%	20.87%	14.78%	4.06%
	(0.4)	(1.6)	(2.2)	(2.4)	(2.2)	(1.9)	(1.1)
B	0.00%	7.33%	16.75%	13.09%	27.75%	29.84%	5.24%
	(0.0)	(1.9)	(2.7)	(2.4)	(3.2)	(3.3)	(1.6)
Caa	0.00%	7.02%	5.26%	12.28%	24.56%	29.82%	21.05%
	(0.0)	(3.4)	(3.0)	(4.3)	(5.7)	(6.1)	(5.4)

Table A.12 Four-Year Average Rating Transition Matrix, 1996–2013

	Terminal Rating						
Original Rating	Aaa	Aa	A	Baa	Ba	B	Caa
Aaa	18.27%	40.38%	28.85%	7.69%	2.88%	1.92%	0.00%
	(3.8)	(4.8)	(4.4)	(2.6)	(1.6)	(1.3)	(0.0)
Aa	6.13%	38.29%	25.60%	16.85%	9.41%	2.41%	1.31%
	(1.1)	(2.3)	(2.0)	(1.8)	(1.4)	(0.7)	(0.5)
A	3.21%	26.07%	33.21%	20.89%	10.71%	5.00%	0.89%
	(0.7)	(1.9)	(2.0)	(1.7)	(1.3)	(0.9)	(0.4)
Baa	1.66%	16.15%	26.50%	26.50%	18.01%	9.32%	1.86%
	(0.6)	(1.7)	(2.0)	(2.0)	(1.7)	(1.3)	(0.6)
Ba	0.61%	10.61%	20.00%	28.48%	23.94%	13.64%	2.73%
	(0.4)	(1.7)	(2.2)	(2.5)	(2.3)	(1.9)	(0.9)
B	0.00%	10.50%	13.81%	24.31%	19.89%	23.76%	7.73%
	(0.0)	(2.3)	(2.6)	(3.2)	(3.0)	(3.2)	(2.0)
Caa	0.00%	1.82%	10.91%	18.18%	25.45%	27.27%	16.36%
	(0.0)	(1.8)	(4.2)	(5.2)	(5.9)	(6.0)	(5.0)

Table A.13 Five-Year Average Rating Transition Matrix, 1996–2013

	Terminal Rating						
	Aaa	Aa	A	Baa	Ba	B	Caa
Aaa	23.60%	40.45%	25.84%	4.49%	3.37%	2.25%	0.00%
	(4.5)	(5.2)	(4.6)	(2.2)	(1.9)	(1.6)	(0.0)
Aa	6.72%	36.32%	26.62%	15.92%	8.46%	4.23%	1.74%
	(1.2)	(2.4)	(2.2)	(1.8)	(1.4)	(1.0)	(0.7)
A	2.89%	26.97%	31.41%	19.85%	10.79%	6.36%	1.73%
	(0.7)	(1.9)	(2.0)	(1.8)	(1.4)	(1.1)	(0.6)
Baa	0.86%	19.87%	24.62%	29.16%	16.85%	6.70%	1.94%
	(0.4)	(1.9)	(2.0)	(2.1)	(1.7)	(1.2)	(0.6)
Ba	0.63%	11.32%	22.33%	25.79%	25.16%	13.21%	1.57%
	(0.4)	(1.8)	(2.3)	(2.5)	(2.4)	(1.9)	(0.7)
B	0.57%	9.77%	14.94%	24.14%	20.69%	24.14%	5.75%
	(0.6)	(2.3)	(2.7)	(3.2)	(3.1)	(3.2)	(1.8)
Caa	0.00%	8.00%	16.00%	18.00%	16.00%	30.00%	12.00%
	(0.0)	(3.8)	(5.2)	(5.4)	(5.2)	(6.5)	(4.6)

Table A.14 Actual One-Year Migration Matrix, 2013–2014

	Aaa	Aa	A	Baa	Ba	B	Caa
Aaa	0.00%	50.00%	50.00%	0.00%	0.00%	0.00%	0.00%
Aa	6.78%	69.49%	22.03%	1.69%	0.00%	0.00%	0.00%
A	1.82%	16.36%	40.00%	29.09%	10.91%	1.82%	0.00%
Baa	0.00%	9.09%	9.09%	54.55%	18.18%	9.09%	0.00%
Ba	0.00%	11.11%	0.00%	33.33%	44.44%	11.11%	0.00%
B	0.00%	0.00%	0.00%	50.00%	25.00%	25.00%	0.00%
Caa	0.00%	0.00%	0.00%	0.00%	50.00%	0.00%	50.00%

Table A.15 One-Year Average Migration Matrix, Prime Scale, 1996–2013

	Prime	Not Prime
Prime	86.39%	13.61%
	(0.8)	(0.8)
Not Prime	43.47%	56.53%
	(1.9)	(1.9)