Farm Financial Persistence and Characteristic Analysis

by

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Abstract

Farmers and agricultural lenders often seek the ability to identify positive or negative characteristics to improve farm operations. Determining these characteristics has been the goal of many research studies. More often than not, a unique set of uncontrollable events was credited for contributing the majority of one farm's success relative to their peers. The goal of this study was to evaluate the assumption that farmers can control their financial persistence defined as remaining in their current financial category, based upon a farm's debt to asset ratio (D/A), and net farm income per acre (NFI $acre^{-1}$). Financial categories give agricultural producers a concrete answer to the question of one farm's ability to maintain their financial persistence during market downturns and poor growing conditions and include Favorable, Marginal Income, Marginal Solvency, and Vulnerable.

Farmers across the United States are subject to many uncontrollable variables (temperature, precipitation, market volatility, land value fluctuations, interest rates) leaving them vulnerable to agricultural market downturns, such as the one that began in 2014. Seasonal cash inflows and outflows of farms and their profitability create a difficult situation for farmers and agricultural lenders alike to predict the future. Identifying and estimating the likelihood of financial persistence has become an area of interest for farmers, their advisors, and their financial lenders. Currently, agricultural lenders rely on loan assessment techniques, such as net present values and loss-based methods. These techniques fail to account for the unique and often long-term investment nature of farming. If an additional method for identifying at-risk farms or at least understanding the likelihood of persistence in farms could be found, it would provide an insight into the

riskiness of lending to a farm and provide agricultural lenders with an additional analysis tool.

The dynamic nature of farm financials and the ever-changing variables of farming limit traditional statistical methods. Considering the difficulty associated with predicting farm default rates due to the complexity of the question, a secondary approach is possible. This study utilized an approach in determining farm financial persistence by estimating the Markov Chain probabilities of four financial categories ranging from Favorable, solvent with positive income to Vulnerable, an insolvent and negative income financial position. Kansas Farm Management Association (KFMA) data from 1993 to 2014 were used to estimate the probability of transitioning between financial categories.

This thesis combines transition probabilities of Kanas farms and a multinomial logit model (MNL) to identify farm characteristics of significance. The matrix of probabilities generated, when interpreted, provide information about Kansas farms and their probability of financial persistence, and the MNL model allows for insights into favorable or un-favorable farm characteristics. Farms were found to transition easily between financial categories that had the same debt to asset ratio (D/A), but different net farm income per acre (NFI $acre^{-1}$, positive or negative) indicating that farm income is more easily changed than farm D/A ratios. Farms in the Favorable category (D/A < 0.4, + NFI $acre^{-1}$) had the largest probability of financial persistence at 0.83, whereas Vulnerable farms (D/A > 0.4, - NFI $acre^{-1}$) were most likely to transition to the Marginal Solvency category (D/A > 0.4, + NFI $acre^{-1}$) with a probability of transitioning of 0.55 versus the probability of remaining in the Vulnerable category of 0.33. It was also found that crop mixture and age were not statistically significant in the MNL model, but gross profit margin and a farm’s percentage of owned land out of total crop acres were statistically significant in explaining why farms were in each category.

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Chapter 1 - Introduction

Agriculture is a cyclical industry that creates alternating highs and lows. This instability leads to financials difficulties for producers and their short term cash flows. In the following thesis, estimation of financial persistence and the likelihood of remaining in a certain state will be investigated. The proceeding chapter provides synopsis of the current agricultural climate.

1.1 Farm Financial Persistence

When a farm is more likely to remain in its current financial category than the chances that it switches to another financial category, it is said to be persistent. When the probability that a farm switches between financial categories is higher than the likelihood of remaining in the current financial category then persistence is absent. Financial persistence is a desirable characteristic when a farm is in a favorable category; and may be interpreted as the farm being managed by a farmer with above average skills. Conversely, financial persistence in an unfavorable category is not a desirable characteristic; and can be attributed to farm characteristics and other exogenous factors. The lack of persistence across all categories may indicate factors outside the control of the management ability of the farmer.

The overall goal of this thesis was to report transition probabilities for Kansas farms assigned to financial categories and identify statistically significant farm characteristics that impacted a farm's financial category assignment. Characteristics of farms in each category and the likelihood of financial persistence in their current category were of interest. Substantially higher levels of financial persistence in the favorable categories compared to the financially unfavorable categories with respect to debt and income indicate management, rather than unique uncontrollable events resulting in farms consistently outperforming their peers. Further information about which farm characteristics effected a farm's financial category was estimated using a multinomial logit model to estimate statistical significance of farm characteristics.

1.2 Current Agricultural Outlook

By 1980 farm expansion was rapidly increasing with farmland as a proportion of farm debt peaking in 1985. The U.S. Farming Crisis of the 1980s led many farmers to default on loans, but it was not only the farmers that suffered during this time. The years from 1987 through 1989 saw as many as 200 bank closures per year (Thompson, 1991). Leading up to this crisis a large amount of farms used low interest rates to quickly expand, however, a change in interest rates made their debt nearly unserviceable. Figure 1 depicts the percent of farm debt that can be attributed for each year from 1960 to 2016 to long-term land based assets. The highest proportion of farm debt attributed to land was in 1985. After this peak in land debt, lenders began working on ensuring farm solvency and projected cash flows indicating a farmer could manage financial stress, such as market volatility.

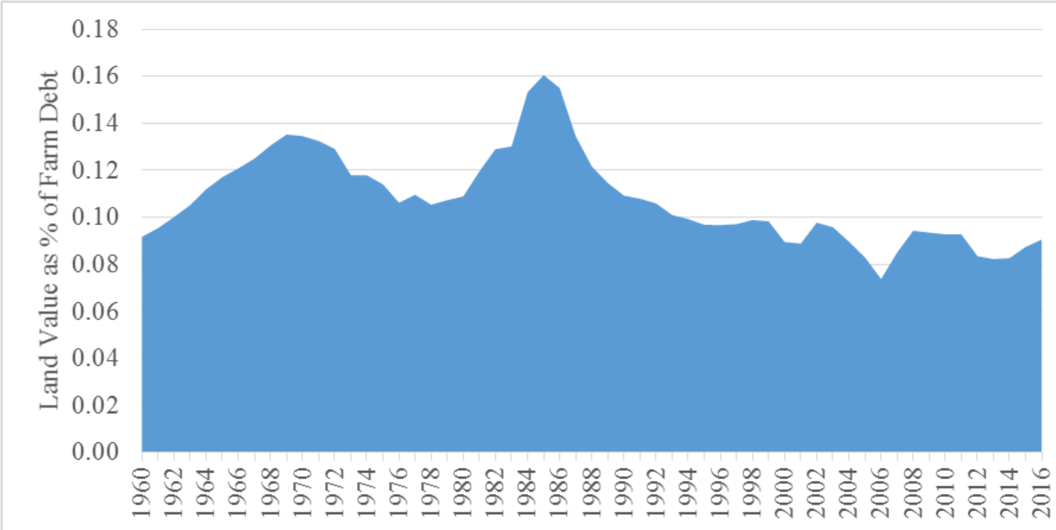

Figure 1. Land Value as Proportion of Farm Debt (1960-2016) (UDSA ERS, 2016)

Kansas farms are facing financial stress similar to the 1980s U.S. farm crisis. In 2013 Kansas as a state ranked as high as sixth in the nation during its peak for net farm income of $5,914 M (USDA, 2015). As of 2015, Kansas fell to 15th nationally, with a net farm income of $1,756 M (USDA, 2015). These changes in rank indicate that not only has Kansas farms followed the commodity crash, but have lost more agricultural production value relative to other states.

At the beginning of 2016, the prices for the primary grain crops in Kansas, wheat, corn, grain sorghum, and soybean, were near the lowest level in nearly a decade. The price levels of all four major commodities were near the ten-year low of $5.88 per bushel, $3.67 per bushel, $3.81 per bushel, $8.01 per bushel for wheat, corn, grain sorghum, and soybean, respectively (USDA, 2016). At harvest, 2016 wheat was selling for $3.74, corn sold for $3.08, grain sorghum was as low as $2.71, and soybean sold for $9.73 per bushel (USDA NASS, 2016).

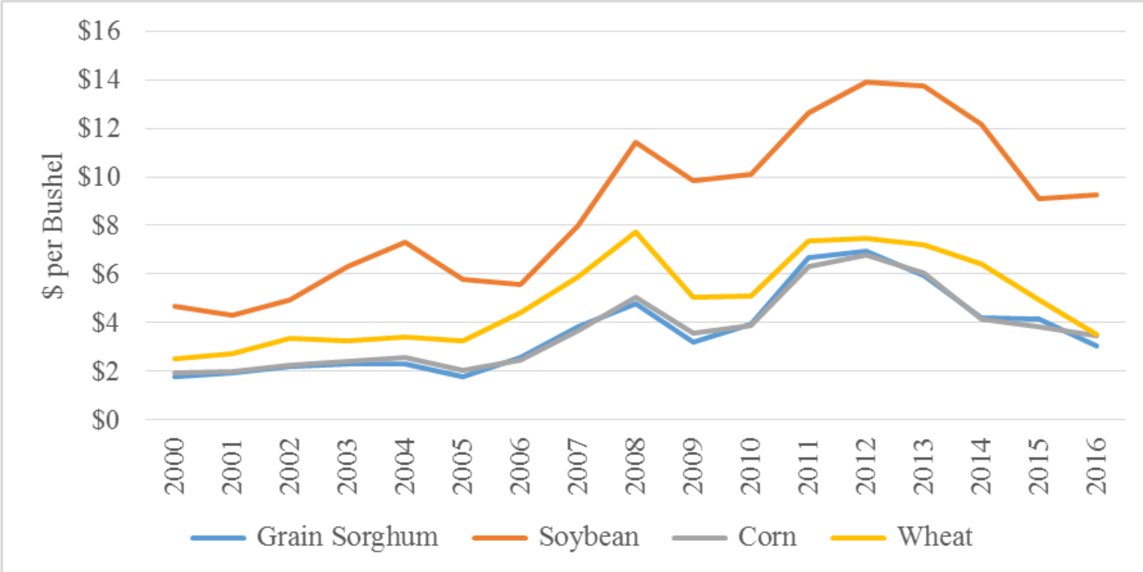

Figure 2. Kansas Annual Grain Prices Received (USDA, NASS)

Several key factors have impacted the value of commodities and decreasing price levels. Relative to other international agricultural exporters, the U.S. dollar value is lowering American export potential. The slowing growth in developing countries (primarily in China and African countries) is adding to decreased demand for U.S. agricultural exports (Cooke et al., 2016). These events are strong fundamental drivers that can drastically alter supply and demand; much more than protein based commodities of beef, pork, and chicken (Cooke et al., 2016). The corresponding effects for Kansas farms is therefore extremely important to farmers, and agricultural lenders alike that primarily serve crop farm communities.

1.3 U.S. Dollar Strength

From 2003 through 2012, the U.S. dollar went through a series of events that caused it to depreciate (Cooke et al., 2016). The stimulus funding used by the federal government during this time to alleviate some of the effects of a slowing U.S. gross domestic product (GDP) added to the trend of devaluation. Figure 3 indicates large spikes in U.S. agricultural exports during 2007 and 2008. The gains in agricultural exports were mostly due to the depreciation of the U.S. dollar and the downgrading of the U.S. credit score (Gong and Kinnucan, 2015). In corn, exports in millions of dollars rose from \$6,991.7M in 2006 to \$13,431M in 2008, a difference of \$6,439.3M (USDA, NASS 2016). Wheat exports in millions of dollars rose from \$4,194.5M in 2006 to \$11,290.3M in 2008, a difference of \$7,095.7M (USDA, NASS 2016). The largest increase came from soybean. Soybean exports in millions of dollars rose from \$6,273.6M in 2006 to \$15,430.9M in 2008, a difference of \$8,495.3M (USDA, NASS 2016). Finally, grain sorghum exports along with other feeding grains (oats and barley) increased from \$3,813.6M in 2006 to \$6,360.4M in 2008, a difference of \$2,546.8M (USDA, NASS 2016). Due to the current strengthening of the U.S. dollar, agricultural exports are losing competiveness against other exporters. Instead of the dollar depreciating, it is gaining in value due to global uncertainty and the perceived notion that the U.S. dollar is going to maintain its value over time. The British referendum to leave the European Union in 2016 was one of the most visible influxes of investors seeking a currency other than the pound (Gillespie, 2016). As the U.S. economic growth has slowly increased and the Federal Reserve has increased the interest rates incrementally, more and more perceived value is being added to the dollar. Due to this, the stock market has reached record levels continuing to increase the strength of the dollar. All of these events have had a positive effect on U.S. currency, but dollar strength and agricultural exports are inversely related. In 2015, corn (-27%), wheat (-22%), and soybean (-21%) are shown to have a substantial visible decrease in export levels (USDA, NASS 2016).

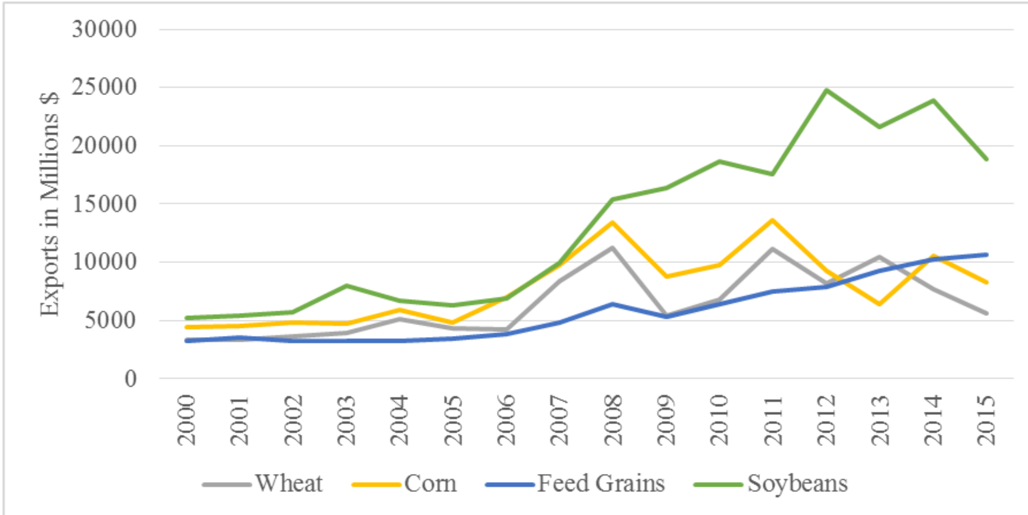

Figure 3. U.S. Total Exports (USDA, Foreign Agricultural Service, 2015)

1.4 Agriculture Lending

Currently, agriculture and specifically grain producers are experiencing suppressed commodity prices leading many in the banking industry to question the overall health and financial standing of Midwestern crop farms. Prices received by farmers for corn and grain sorghum have dropped by as much as 50%, wheat prices have fallen by 48%, and soybean has decreased by 35% since 2013 (Figure 2) (Kauffman, 2016). With tightening margins, farmers have worked towards increasing their production efficiencies and decreasing waste. Farms' net farm income ratio (ratio of income to value of production) and expense ratio have fallen at different rates. Despite farmers' efforts, the expense ratio has been falling slower than the net farm income ratio indicating smaller profitability (O'Brien and Yeager, 2017). Another indicator for financial health is working capital burn rates because they represent a farm's ability to absorb losses given long downturns in the commodity markets (O'Brien and Yeager, 2017). The change in working capital comparing the last three years shows that farms are beginning to 'burn' through their reserves. The vast majority of farms in 2015 and 2016 experienced modest deterioration in their working capital (Kauffman, 2016). In 2015, 15% more farms were designated having modest deterioration in working capital than in 2014, and in 2016 an 18% increase in farms designated with significant deterioration of working capital (Kauffman, 2016). O'Brien and Yeager found that 44% of Kansas producers were observed having calculated burn rates of less than 5 years 2017).

Since land values often make up a large share of a farm's total asset value, any change to land prices could be devastating. Prior to 2016, Kansas non-irrigated farmland gained in value by 21% annually beginning in 2010 (Taylor et al., 2015). With a long-term average growth in land prices of 3% instead of 21% a decrease in the price of farmland seems plausible. Low interest rates, high crop returns, and limited alternative vehicles of investment were the key reasons for the growth in price (Taylor et al., 2015). In 2015 land price growth shifted and values began to fall. Griffin and Taylor (2017) used a land index to analyze trends in the Kansas land market. They found that values peaked in 2014, but since then have softened decreasing on average 7% in 2015 (Griffin and Taylor, 2017). Cash rents follow crop prices more than land values and will typically have more elasticity (Ibendahl and Griffin, 2013). Land rents in 2016 decreased by 10% relative to the previous year and are expected to continue decreasing, which should help alleviate some of the producer's expenses (Kauffman, 2016). These changes in cropland values and rents create a paradigm shift for agricultural lenders who must reassess the financial soundness of their clients.

Despite all of the downward pressure driving down farm income over the last two years only a minor uptick in past-due loans has occurred (Kauffman, 2016). Featherstone and Langemeier (2015) analyzed credit deterioration of Kansas farms and reported default probabilities of Kansas Farm Management Association (KFMA) members across the state increased for all categories except producers that specialize in cattle production (See Cow Herd, Table 1). These increases indicate that agricultural lenders should be scrutinizing their loan portfolios for farmers exhibiting risky behavior (Table 1).

Table 1. Estimated Probabilities of Loan Default

Farm Type	2014	2015
Crop – Non-Irrigated	1.5%	1.89%
Crop – Irrigated	1.86%	2.26%
Crop – Beef	1.5%	1.97%
Crop – Beef Backgrounding	1.87%	2.51%
Crop – Cow Herd	1.14%	1.39%
Cow Herd	1.76%	1.65%
Dairy	1.69%	1.89%
General	1.11%	1.20%

Source: Featherstone and Langemeier, 2015

Chapter 2 - Literature Review

The procedures utilized to estimate the financial probabilities are not novel. However, their application to Kansas Farm Management Association data using four specific financial categories are new. The following chapter summarizes the previous research that laid the ground work for this research.

2.1 Markov Chain Probabilities

In 1907, Andrey Markov began utilizing conditional probabilities that focused on previous standing in order to predict future changes, and this became known as Markov Chain probabilities (Cameron and Trivedi, 2005). Following Andrey Markov's creation, other statisticians began using his method to predict a variety of scenarios. Fields of study, such as, epidemiology, population growth, and agriculture found them useful.

Markov Chain probabilities can be used for a wide range of scenarios. The endogenous nature of this procedure lends itself to biological events that have unlimited variability in settings. Therefore, Markov Chain probabilities that only take into consideration a designated number of previous states can be useful. Some examples of use are predicting: epidemics, pest population growth, harvesting natural resources (timber, fish, cattle, etc.), and human problems (for example abortion rates, poverty and availability of contraceptive drugs) (Jaquette, 1972). In a survey performed by White (1993), 18 different categories of use were found. These categories vary from biological, mechanical, financial, and spatial fields of study. The easiest way to describe all of them jointly is as decision models because each one represents a decision made voluntarily or involuntarily to transition to a future state of being. This cursory search done over a decade ago is a small sample of Markov Chain probabilities in research today.

Table 2. Summary of Markov Chain Probabilities Applications (White, 1993)

Category	Number of Studies
Population Harvesting	5
Agriculture	5
Water Resources	15
Inspection, Maintenance, and Repair	18
Purchasing, Inventory, and Production	14
Finance and Investment	9
Queues	6
Sales Promotion	4
Search	3
Motor Insurance Claim	2
Overbooking	5
Epidemics	2
Credit	2
Sports	2
Patient Admissions	1
Location	1
Design Experiments	1
General	5

Source: White (1993)

Statistical models often only depict the intensities of an event frequency, but in the case of Markov Chain probabilities they represent the likelihood of occurrence based upon current status (Andersen et al., 1991). For example, in the medical field Markov Chain probabilities are used to determine patient health and foresee potential transitions to undesired states (Jung, 2006). Feldman and Curry (1982) determined mathematical approaches to agricultural problems could be viable by using Markov Chain probabilities to estimate pest populations and identify economic thresholds, which indicated the need for implementation of mechanical, biological, chemical, or cultural controls.

According to Burns et al. (2015), a financial environment similar to the U.S. farm crisis of the 1980s could potentially arise under a specific set of conditions. They cite falling land prices in 2014 coupled with lower commodity prices along with smaller net farm incomes as potential sources of distress. Although a crisis could arise, the USDA Agricultural Income and Finance Outlook indicated that estimates for farm debt to equity and debt to asset ratios would continue to decrease allowing farms to maintain financial persistence (Park et al., 2010). However, the negative farm outlook has many agricultural lenders and farmers asking about farm financial persistence. With the complex and constantly changing variables related to agricultural production, Markov Chain probabilities are suited for identifying the likelihood of transitioning to an undesirable financial category.

2.2 Farm Management and Characteristics

Despite the expected persistence reported by Park et al. (2010), recent changes in net farm income have exposed farmers to financial instability. As of 2016 USDA, ERS net farm income forecasts indicate that farming income will continue to decline (USDA, ERS 2016). Consequently, considerable interest has been focused on the ability to identify farms with above average managerial performances; however, identifying and quantifying managerial performances provides a unique set of problems. Sonka et al. (1989) attempted to identify proxies for managerial variables using statistical analyses of Illinois farm data from 1976 to 1983. Overall, characteristics thought to be significant (farm size and cropping pattern) were not found to be significant in determining performance (Sonka et al., 1989). Ford and Shonkwiler (1994) used maximum likelihood estimators to find variables of interest and confirmatory factor analysis. This research study wasn't directed at crop farms, but was directed at Pennsylvania dairies. Counter to Sonka's finding of farm size being insignificant herd size was considered a highly significant regressor (Ford and Shonkwiler, 1994). This leads to the consideration that benefits from economies of scale in one agricultural industry may not translate to another. Goodwin et al. (2002) used Kansas farm data with two goals in mind including 1) determining the roles that experience and learning plays in determining yield performance and 2) quantifying the magnitude of these variables of interest and their impact upon yield performance. They discovered that a producer that typically had above average yields in one crop was unable to transfer the "general" experience into growing another crop and generating above average yields showing that experience with specific crop productions were correlated with yield (Goodwin et al. 2002). Yeager and Langemeier (2011) applied nonparametric data envelopment analysis (DEA) to Kansas farm data while focusing on operator age and its relationship to technical efficiency while looking for the convergence or the divergence of farm performance over time. Yeager and Langemeier found that age played a role in a farm's efficiency, but only to a certain point; in the last 10 years of production farms were shown losing efficiency (Yeager and Langmeier, 2011). Mishra et al. (2009) utilized returns on assets as a measure of managerial performance with a focus on farm operator characteristics, farm production and marketing efficiency, and other management techniques. This study added to the validity of Yeager and Langmeier's conclusions that age had an inverted U-shaped relationship to performance. It also found that having a written business plan can lead higher financial performance (Mishra et al., 2009). Zech and Penderson (2003) utilized logit regression analysis to find characteristics linked to loan repayment ability while comparing their results to previous studies. Zech and Pendedrson found that debt to asset ratio was important to estimating a borrower's creditworthiness and that a specific set of years wasn't applicable to a different unique time period.

These research studies jointly add to the need for utilizing Markov Chain probabilities and MNL to identify characteristics of significance. Many different approaches exist when trying to explain farm management's impact on farm success. The identification of managerial variables and their impacts from these above-mentioned research articles lend themselves to this research. One of the first metrics useful in evaluating farm management performance is the persistence with which farm businesses remain profitable.

2.3 Predicting Farm Financial Default Rates

Farmers are not the only beneficiaries of this study; Markov Chain probabilities estimated for Kansas farms transitioning among four different financial categories would be beneficial to agricultural lenders. Farming is a highly capital intensive enterprise that is also subject to volatility because 87% of that capital consists of land and equipment

(Katchova and Barry, 2005). Simplistic approaches have been attempted to identify at-risk farms. Zech and Penderson (2003) attempted to use term debt coverage ratio and net worth growth ratio incorporated into regression analysis to estimate farm financial health. The analysis indicated that models created by using one-time period were not applicable for forecasting borrower financial performance and repayment ability in another time period (Zech and Penderson, 2003). This uncertain nature was attributed to lengthy production cycles and less frequent or seasonal repayment (Katchova and Barry, 2005). Another approach offered by Featherstone et al. (2006) used data from the 7th Farm Credit district and Standard and Poor's credit methodology to find default rates within 157,853 different loans. They found that the average probability of default within this loan portfolio was 1.61% (Featherstone et al., 2006) (Note that Kansas was not part of the data set, but some of the results are transferable). Given the prediction that 35% of debt value is lost when a farm defaults creates a poor outcome when these events occur (Katchova and Barry, 2005). Xiaohui et al. (2007) used Markov Chain models and compared results to traditional discrete-time (cohort) methods. Migration analysis (extrapolation of historic movement rates among risk classes) is widely adopted in corporate finance. This system is inadequate for agricultural applications because the shorter data histories and poor quality of financial data create estimates that are inaccurate (Xiaohui et al., 2007). Xiaohui et al. (2007) found that utilizing Markov Chain models created a more accurate estimation of movement amongst credit risk rating classes for agricultural firms.

2.4 Farm Persistence

Farm profitability persistence has been evaluated in Illinois (Kuethe et al. 2015; Li and Paulson, 2014; Urcola et al., 2004) and Kansas (Herbel and Langemeier, 2012; Ibendahl, 2013, Griffin and Ibendahl, 2015, Stabel et al., 2018). Urcola et al. (2004) focused on agronomic yield rather than profitability. Urcola et al. (2004) and Ibendahl (2012) discussed their results in terms of management skill versus an underlying stochastic process, i.e. controllable and uncontrollable factors. These previous studies of farm management association records programs can be considered comparative analyses, comparing and contrasting characteristics of the most and least profitable groups. Li and Paulson (2014) continued the use of Illinois data by expanding the time horizon of Urcola et al. (2004) and correcting for survivor bias. They reported that in 5% of managers have more efficient skills to outperform the county average in the long run. Langemeier and DeLano (1999) applied data envelopment analysis to a 24-year panel from the KFMA databank. Additionally, they also found that some farms appear to benefit from natural endowments of soil productivity or farm size (Langemeier and Delano, 1999). Ibendahl (2012) expanded upon the Kansas study by evaluating farms allocated to decile groups based on profitability. Ibendahl reported that controllable factors only explained a portion of the financial rankings suggesting that uncontrollable factors had a substantial role. Using a different approach, Nivens et al. (2002) investigated how a farm varied relative to the average observation derived from the sample data (Kansas farms 1990-1999) in the following categories: profit, input cost, yield, crop price, technology adoption, seeding rates, farm size, government payments, and risk (Nivens, 2002). The following categories were found to have the largest impact upon farm profitability: input costs, yield, and seeding rates.

Given the comparisons between most and least profitable categories, the next logical question to address was the probability of farms transitioning between profitable categories or remaining in their current category. Kuethe et al. (2015) evaluated farm financial persistence with respect to financial vulnerability that focused on farm's debt to asset ratios and net farm income. The probability of remaining in the highest (lowest) profitability state can be estimated using ranks across multiple years; Markov Chain transition probabilities (Eddy, 1998) have been applied to 1) soil erosion classification (Skaggs and Ghosh, 1999), 2) livestock farm size (Gillespie and Fulton, 2001), 3) health and medicine (Jung, 2006), and 4) land use changes (Muller and Middleton, 1994). In a study by Stabel et al. (2018), Markov probabilities were applied to Kansas farm profitability data. Another use of Markov Chain probabilities applied to KFMA data identified the probability of farm technology adoption rates (Griffin et al., 2017). Building upon Griffin and Ibendahl (2015) and Stabel et al., (2018), this study created more rigid metrics for determining financial persistence and farm persistence instead of using profitability as a proxy for farm health, and also attempted to identify key characteristics of successful farms.

Chapter 3 - Data

Kansas Farm Management Association is a wealth of data that can be relied upon to create an image of the Kansas agricultural environment. It encompasses farms of all sizes and geographical regions. In fact 80 years of data and 6 distinct management zones over the state of Kansas are used to generate the information in the KFMA databank. By using this data set the results are more applicable than without it.

3.1 Data Collection and Scrubbing

The results of this thesis were generated by analyzing data from the Kansas Farm Management Association (KFMA). Over the 22-year period from 1993 to 2014, approximately 2,397 or more farms were annually available for Markov transition probability analysis. A subset of 260 farms over the years 2000 to 2014 was created for the multinomial logit model. The KFMA data set is composed of farms from six different associations: North Central, South Central, South West, North East, North West, and South East (Figure 4). Data has been collected for many decades and records since 1973 electronically available. Currently 25 Kansas State University agricultural economists work with farmers to continue this collection process. They collect up to 2,370 different variables for approximately 2,000 farms annually creating an valuable tool for Kansas farm economic research (Ibendahl, 2017).

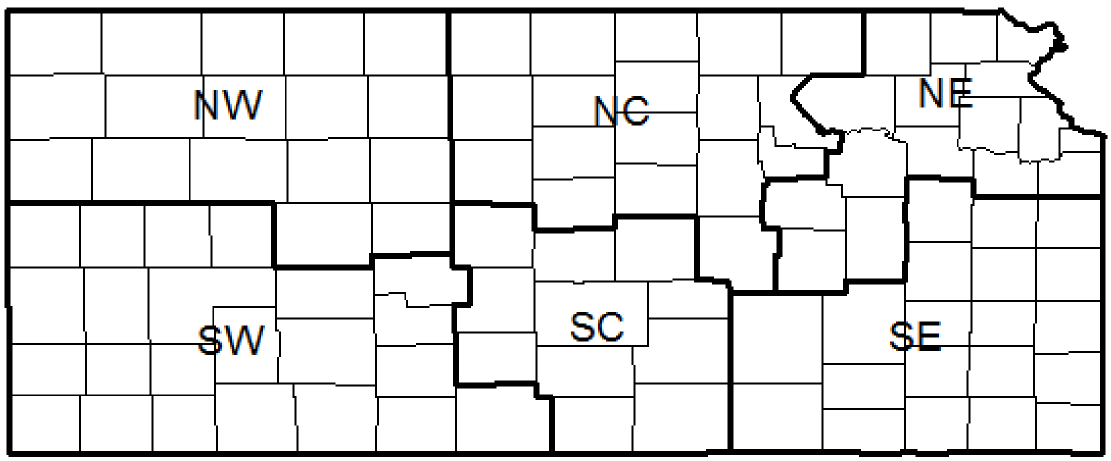

Figure 4. The Six Kansas Farm Management Association Regions

Utilization of this data set required several steps to insure the validity of each observation. Contained within the data bank is a variable (variable V007) used by KFMA economists to flag data that may be incomplete or atypical of the region or county (Langemeier, 2010). Once observations flagged for incompleteness were sorted out the next step was to remove farms without crop acres. These were farms that either did not have any crop acres or were considered livestock farms. This was an additional chance to check for completeness of the record. Farms that were primarily irrigated crop farms were eliminated so that farms that were exposed to minimal weather risk were omitted.

3.2 Land Price Data

The KFMA database updates land values once every five years. Therefore, due to the nature of the sampling, this cyclic sampling method created an issue when calculating accurate debt-to-asset ratios. Data used for this task came from two separate sources. Data from the KFMA and USDA NASS (National Agricultural Statistics Service) were utilized to correct for the periodic update method applied by KFMA.

Non-irrigated cropland values were derived from the information provided from the KFMA members. During the years of interest from 1993 to 2014, land values from 2,397 farms were available. In order to insure that correct land values were being used to calculate debt-to-asset ratios a second source was needed. Each August, USDA NASS reports state-level results on surveyed agricultural real estate and cropland values. The annual survey is conducted using a complete, probability-based land-area sampling frame with a sample size of 11,000 farms (NASS, 2017). For each state, the annual cropland values are reported in August. The NASS data were then combined with the KFMA data to provide an estimate of land values.

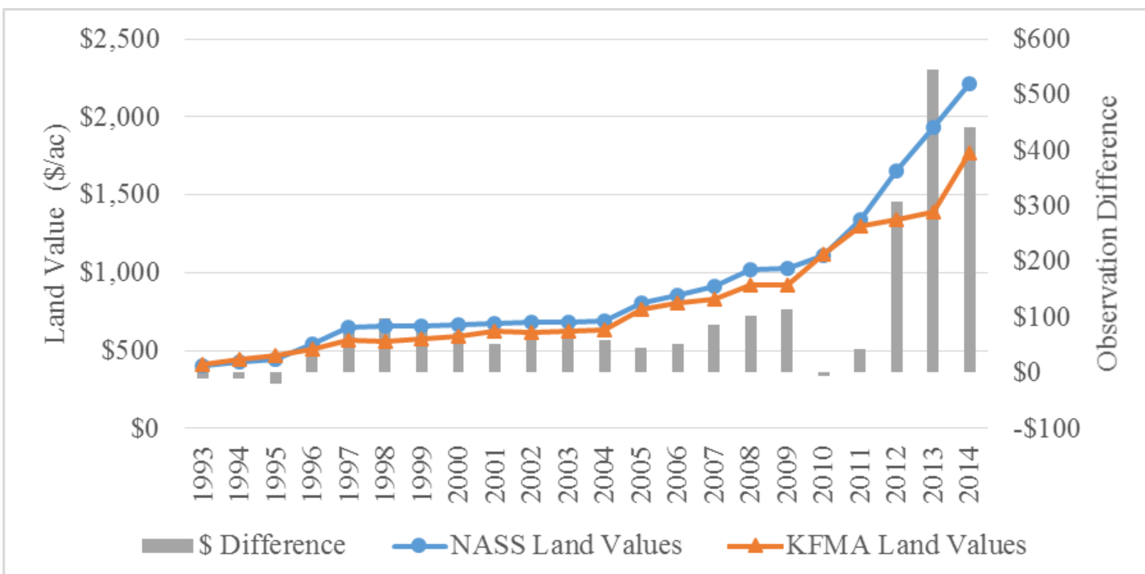

Figure 5. Kansas Agricultural Real-Estate Value Comparison

Figure 5 depicts the two different land value data sets relative to each other. The NASS land values were typically higher than KFMA land values (prior to adjustment). The 5-year sampling method is visually apparent in years where an update was made. For example, in 2010 the grey bar depicting the difference in dollars between the two price data sets is only $5.96, whereas years in between the updates the difference widens. The secondary y-axis details the difference between NASS and KFMA land values (Figure 5). During the rapid land value increases following 2008, KFMA land values estimates did not closely track NASS values.

To calculate accurate land values, the data were cleaned to remove any values deemed outliers. The first step was a general inquiry by applying logical assumptions to remove the easily discernable outliers. Farms with land values of $0 per acre were assumed to be a transfer or sale between related parties. Several farms located near major metropolitan areas such as Wichita and Kansas City had reported farm land values that were not representative of agricultural value of land, i.e. speculative value were not incorporated. These values were caused by urban sprawl, speculative growth, and potential commercial use. The second step was to create an allowance of 90% of the NASS land values and establish a reasonable range. Anything left after the commercial outliers were removed was sorted by the above mentioned criteria. This procedure culled 6,864 farms leaving 21,431 unique farm records over the timespan to be utilized in the development of the KFMA recorded land values.

The land price data over time changed with varying rates, but was positive in all but seven years. Figure 6 depicts growth in land values since 2004 were similar to the land value growth seen in the 12 years preceding the U.S. farm crisis of the 1980s.

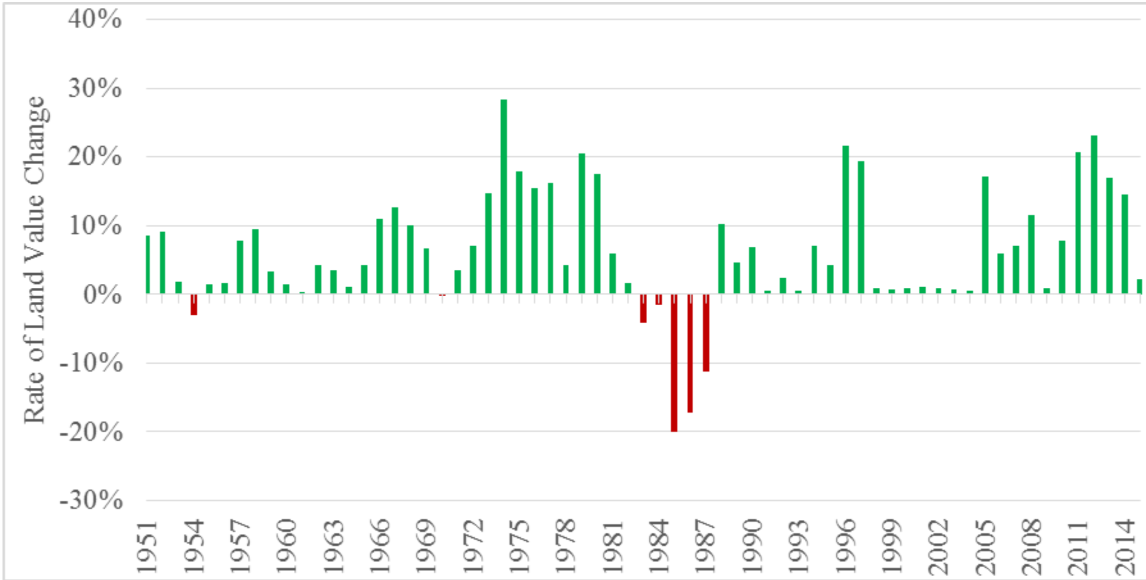

Figure 6. Annual Land Value Change Rate

3.3 KFMA Member Summary

The KFMA data set of 2,397 unique farm records was used to estimate the Markov Chain probabilities. This data included farms from across Kansas with a relatively larger portion (27%) coming from the Southeastern region. Both Western regions were sparsely represented compared to the remaining regions with the Northwest and Southwest regions making up 9% and 8% of the observations, respectively. The distribution of members for each of the six KFMA associations are presented in Table 3.

The state of Kansas is geographically and climatically diverse. Due to this statewide variation, agricultural economic research is subject to regional bias caused by disproportionate spatial sampling. The average Kansas farm within this study was 1,429 acres with an operator age of 53.95 years. Wheat is the primary crop at 47% of reported acres followed by soybean (29%) and corn (22%). A breakdown comparing the regional crop mixtures for the six KFMA associations indicated that the increased number of South East Kansas farms causes soybean acres to be overly exaggerated.

Table 3 Geographical Farm Distribution (1993-2014)

KFMA District	Number of Observations	Percent of Farms
Southwest	193	8%
Northwest	216	9%
North Central	407	17%
South Central	527	22%
Northeast	407	17%
Southeast	647	27%

Operating expense, percentage of owned land, NFI acre^{-1}, D/A ratio, and gross profit margin for each farm were recorded. Operating expenses were calculated using the gross farm income method, except for interest paid (Langemeier, 2010). Operating expenses can change drastically with farm size, but the mean for the time period was $256,678 with a gross profit margin of 9% and a net farm income per acre of $51.73. Kansas farms in the data set were below the benchmark of 0.4 D/A ratio with 0.36 D/A ratio being the estimated mean.

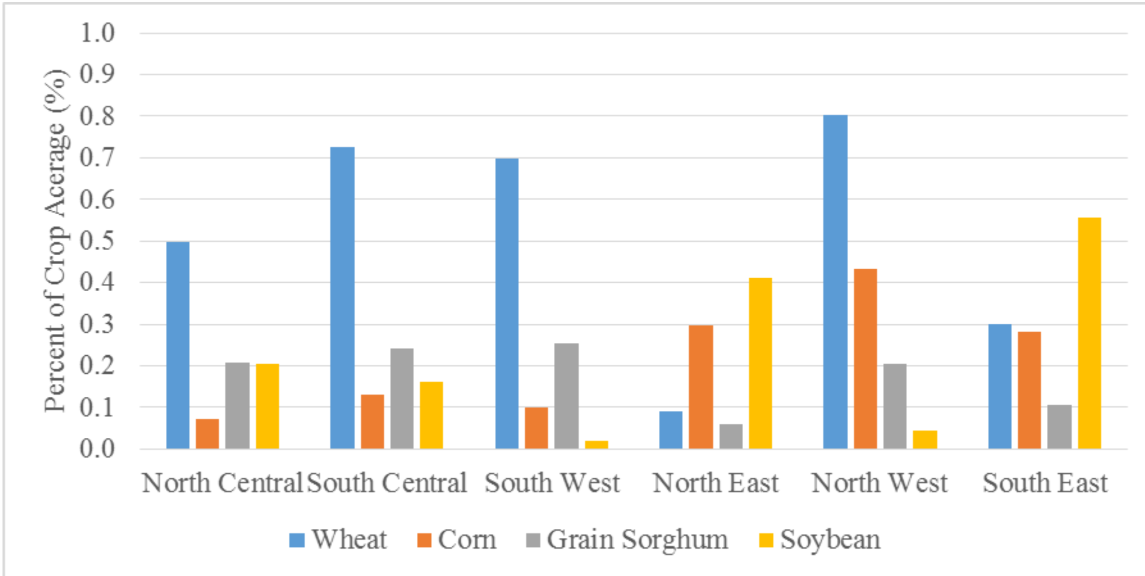

Figure 7 KFMA Regional Crop Mixture (1993-2014)

A comparison of regions highlights North East and South East Kansas for above average NFI acre^{-1} (Figure 8). The increasing gradient of rainfall amounts, moving west to east, likely creates greater production capacity and as a result greater NFI acre^{-1}. Although western Kansas farms generate less NFI acre^{-1}they maintain lower D/A ratios than all other regions.

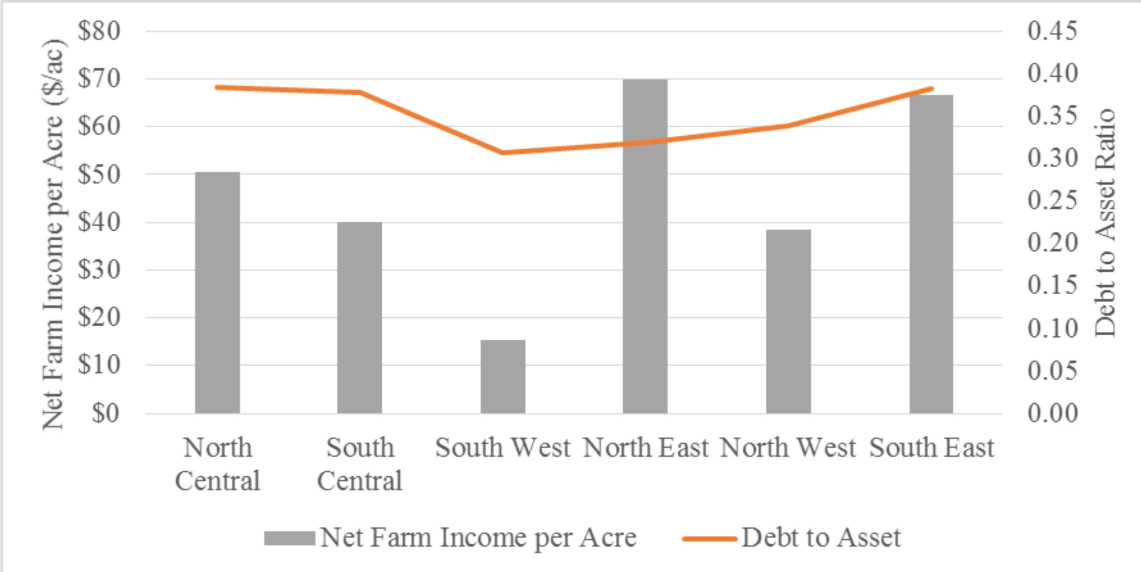

Figure 8. Average KFMA Net Farm Income per Acre and Debt to Asset Ratios (1993-2014)

3.4 Multinomial Logit Regression Data

A balanced series of data were required for the second step of analysis. From the unbalanced data set, a balanced sample set was created to facilitate the multinomial logit regression. Multinomial logit regression is used to depict relationships between multiple outcomes and a set of regressors (Kufeld and So, 1995). The timeline was shortened from 22 years to the most recent 15 years to acquire an accurate representation of current farm characteristics. From 2000 to 2014 only 260 farms were available continuously in the KFMA records. The 260 observations differed from the statewide unbalanced set slightly. Comparison of summary statistics of key variables between the unbalanced and balanced samples are presented in Table 4.

Table 4. Descriptive Statistics for Balanced and Unbalanced Datasets

Variable	Unbalanced Sample Mean (1993-2014)	Balanced Sample Mean (2000-2014)
% Wheat	0.47	0.36
% Corn	0.21	0.18
% Grain Sorghum	0.16	0.13
% Soybean	0.29	0.31
Acres	1429	1563
Gross Profit Margin	0.09	0.20
Operating Costs	$256,678	$312,509
D/A Ratio	0.35	0.33
NFI acre^{-1}	$52	$65

3.5 Kansas Farmland Index

The first step was to create a Kansas farmland index that corrected KFMA land values within the data set. The Kansas Farm Management Association (KFMA) land values from 1993 to 2014 were only adjusted every 5 years creating a challenge when calculating debt to asset ratios. Farmland assets make up a large amount of total farm assets making it important to have the most accurate values. National Agricultural Statistics Service (NASS, 2016) data for statewide land values were used to remedy the aforementioned complication. Table 5 summarizes the observed land values for each data set.

Table 5 Land Value Estimates from NASS and KFMA

Year	NASS	KFMA	Year	NASS	KFMA
1993	$401	$454	2004	$688	$651
1994	$429	$470	2005	$806	$804
1995	$447	$486	2006	$854	$830
1996	$544	$520	2007	$914	$860
1997	$649	$553	2008	$1020	$906
1998	$655	$563	2009	$1030	$913
1999	$660	$571	2010	$1110	$1203
2000	$666	$608	2011	$1340	$1269
2001	$673	$623	2012	$1650	$1398
2002	$679	$628	2013	$1930	$1482
2003	$684	$630	2014	$2210	$1597

Once an accurate land value was found for each year the difference between the KFMA annual land value ($\mathrm{X_{KFMA}}$) and the NASS annual land values ($\mathrm{Y_{NASS}}$) were calculated by finding the percent difference. Then the original farmland value ($\mathrm{A_{ij}}$) for each farm for that year from KFMA was multiplied by the adjustment to find the new farmland valuation.

$$\text{New Farmland Valuation} = \left(\frac{\mathrm{Y_{NASS}}}{\mathrm{X_{KFMA}}}\right) * \mathrm{A_{ij}} \qquad \textbf{(1)}$$

It should be noted that every five-year interval is simply 100% indicating that no adjustment is necessary for those years because KFMA data were updated during those periods. An example of a value adjustment; in 1993 the average reported value for non-irrigated dryland acres from the KFMA was $454, but the NASS survey found that the value of non-irrigated dryland acres in Kansas was $401. To correct for this difference land asset values for 1993 in the data set were deflated by 12%, thereby giving a more accurate value. This value was then reincorporated into a farm's total assets and used to estimate their true D/A ratio for a given year.

Table 6. Annual Land Value Adjustment

Year	% Difference	Adjustment
1993	88%	-12%
1994	91%	-9%
1995	100%	0%
1996	104%	4%
1997	117%	17%
1998	116%	16%
1999	115%	15%
2000	100%	0%
2001	108%	8%
2002	108%	8%
2003	109%	9%
2004	106%	6%
2005	100%	0%
2006	103%	3%
2007	106%	6%
2008	113%	13%
2009	113%	13%
2010	100%	0%
2011	106%	6%
2012	118%	18%
2013	130%	30%
2014	138%	38%

Chapter 4 - Methods

KFMA members were sorted into four financial categories derived from two key metrics used in the lending industry (Debt-to-Asset ratio and Net Farm Income). Utilizing Markov Chain probabilities, the likelihood of transitioning to the four financial categories based on the prior state was estimated. Then farm member characteristics were analyzed for statistical significance using multinomial logit regression.

4.1 Financial Categories

Four financial categories were defined to assign farms into financial categories. Farms were then categorized by different threshold variables measuring farm performance: Debt to Asset (D/A) ratio and Net Farm Income per Acre (NFI acre^{-1}). Debt to asset ratios have been used when determining the viability of a loan applicant, therefore, it became one of the key determining factors used to categorize farms into different financial categories. A D/A of 0.4 or lower was deemed to be a necessary level where a farm was financially favorable (Kuethe et al., 2015). The second break point was if the farm had a positive NFI acre^{-1} or a negative NFI acre^{-1} (Kuethe et al., 2015). Due to the nature of farming a positive income is not always possible, but a farm that is able to maintain breakeven production costs shows management skills and an ability to properly control for price and production risk.

The USDA Economic Research Service financial vulnerability definition were used to assign each farm to a category for each year that their data was available in the KFMA data set (Hoppe et al., 2007). Farm participation and reporting for the KFMA can be intermittent, in turn leading to an incomplete, yet valuable unbalanced panel dataset.

Once farm observations not meeting the inclusion criteria (explained in Chapter 3) were omitted, 2,397 farms remained for further analysis.

Table 7 Farm Financial Categories

	Favorable	Marginal Income	Marginal Solvency	Vulnerable
Debt to Asset	≤ 0.4	≤ 0.4	≥ 0.4	≥ 0.4
Net Farm Income Per Acre	(+) positive	(-) negative	(+) positive	(-) negative

Farms in the Favorable category were considered to be financially sound with a positive NFI acre^{-1}and a D/A ratio less than the lending industry standard of 0.4 (Table 7). These farms were designated as favorable because of their profitability and their solvent nature. Marginal Income farms were farms with a negative NFI acre^{-1}, but were not highly leveraged with a D/A below 0.4. Marginal Solvency farms were similar to Favorable farms except these farms had a positive NFI acre^{-1}and were considered highly leveraged with D/A ratios exceeding 0.4. Farms falling into the final category, Vulnerable, were farms with negative NFI acre^{-1}and D/A ratios above 0.4 and were the most undesirable category. It should be noted that Favorable, Marginal Income, Marginal Solvency, and Vulnerable farms were not ordinal; in particular, Marginal Income and Marginal Solvency could be considered equivalent ranks pending the risk preference of the decision maker.

Table 8 Number of KFMA Observations by Association and Year before Sorting

Year	North Central	South Central	South West	North East	North West	South East	Yearly Total
1993	119	232	101	204	88	273	1017
1994	133	249	98	209	81	294	1064
1995	147	274	111	203	82	289	1106
1996	163	272	103	205	87	327	1157
1997	169	268	87	218	94	319	1155
1998	211	258	128	204	94	326	1221
1999	195	269	106	205	106	293	1174
2000	217	269	119	191	106	311	1213
2001	197	268	105	197	110	302	1179
2002	197	269	102	195	108	302	1173
2003	190	241	118	203	110	291	1153
2004	191	240	109	188	104	296	1128
2005	190	235	73	154	100	288	1040
2006	186	243	70	139	94	272	1004
2007	183	215	65	158	82	267	970
2008	193	209	60	145	94	281	982
2009	194	216	60	140	92	275	977
2010	179	209	55	137	92	275	947
2011	166	189	42	136	83	279	895
2012	154	182	44	134	64	270	848
2013	159	127	42	128	64	252	772
2014	147	131	39	128	63	193	701

4.2 Markov Chain Probabilities

An irreducible, (able to enter or exit any category in any order) first order Markov Chain was used to estimate the probability of farms either remaining/persisting in their current financial category or transitioning to another category. A one-step transition probability matrix, **P**, from one category to another category was estimated. The transition probability matrix, **P**, is the matrix consisting of one-step transition probabilities, p_{ij}, defined as

$$p_{ij} = \Pr\{X_t = j | X_{t-1} = i\} \qquad \textbf{(2)}$$

where p_{ij} is one-step transition probabilities equal to the probability of being in financial category j given the individual farm was in financial category state i in previous year, t. The underlying assumption of a first-order Markov Chain models is that the state of world today (time t) is only a function of the previous time period (time t-1) (Cameron, 2005). Markov transition persistence or the probability of a farm remaining in a given financial category is referred to as financial persistence in this thesis. The probability of transitioning from one category to any other category was estimated for all farms that were in the KFMA database for all years from 1993 to 2014.

One-step Markov Chain probabilities were estimated under two different settings: an unbalanced data set and a smaller balanced data set. It should be noted that the smaller balanced data set time frame ranged from 2000 to 2014 instead of 1993 to 2014. The first estimation used an unbalanced data set from 1993 to 2014 to estimate the financial persistence.

Since the multinomial logit (MNL) model used to observe the impact of specific farm characteristics on the probability of being in one of the financial categories required a balanced data set it was necessary to rerun the transition probabilities specifically for that data set as well to insure continuity of conclusions made from the unbalanced larger sample. The primary purpose of this was to allow for a comparison between the larger unbalanced data set from 1993 to 2014 and the smaller, but the balanced data set from 2000 to 2014.

4.3 Multinomial Logit Regression

Multinomial logit models (MNL) are used to estimate the relationship between a set of regressor variables and multiple discrete responses (So and Kuhfeld, 1995). This discrete-choice model is used when multiple discrete outcomes arise. The strength of this method is the ability to analyze multiple outcome categories. Multinomial logit models can be divided into two groups: ordered and unordered (So and Kuhfeld, 1995). In the case of this study, farms were assigned to one of four unordered financial categories. This unordered model can be described as the probability (P_{jk}) of the j^{th} individual selecting k^{th} financial category, given the values of X_j (Cameron, 2005).

$$P_{jk} = \frac{\exp(\beta_k' X_j)}{\sum_{l=1}^{m} \exp(\beta_l' X_j)} \quad \textbf{(3)}$$

The coefficient (β_k') of this model is not in a form that is directly interpretable. Consequently, the partial or marginal effects were estimated to provide values of change for each independent variable on the likelihood of being in a particular category. The first derivative of the probability function Π_{jk} yields the marginal effects of the independent variable X_j on the probability of being in the k^{th} financial category.

$$\text{Partial Effect} = \frac{dP_{jk}}{X_{s,j}} \quad \textbf{(4)}$$

There were 260 farms from the KFMA, from 2000 to 2014 used in the MNL model. Financial and structural variables that were most likely to provide intuitive results in identifying farm characteristics were used. Financial variables chosen were: gross profit margin and percentage of owned land. Gross profit margin was chosen because it encompassed production costs and revenue, which in turn related back to NFI acre^{-1}. Net farm income per acre is a variable of interest, but because it was used in categorizing the farms, it's effects in the multinomial logit model were not used. A gross profit margin was deemed acceptable, but the estimates are understood to have potential for bias. The percentage of owned farmland was chosen to compare the proportion of owned land versus rented land related to each category. Variables that were influenced by a cognitive decision on the part of the farmer included: percentage of corn acres, percentage of soybean acres, percentage of sorghum acres, percentage of wheat acres, and farm size. Crop choice was hypothesized to be a major choice for farmers that dictate their NFI acre^{-1} each year. The four major Kansas crops; corn, soybean, grain sorghum, and wheat, are important variables when describing what types of farms were assigned to each category. The number of farm acres was included because the trend in increasing farm size. Three lagged variables were included in the model: Favorable Lag, Marginal Income Lag, and Marginal Solvency Lag, representing the farm's previous financial category, not the previous year per se. The marginal effects for each variable were estimated using Equation 4. The expected signs for each independent variable of interest are listed in Table 8.

Table 8 Expected Independent Variable Signs

Variable	Expected Sign Relative to Financial Category			
	Favorable	Marginal Income	Marginal Solvency	Vulnerable
Age	(+)	(+)	(-)	(-)
% Owned	(+)	(-)	(+)	(+)
% Corn	(+)	(-)	(+)	(-)
% Wheat	(+)	(-)	(+)	(-)
% Soybean	(+)	(-)	(+)	(-)
Gross Profit Margin	(+)	(-)	(+)	(-)
Farm Size	(+)	(-)	(+)	(-)
Favorable Lag	(+)	(+)	(-)	(-)
Marginal Income Lag	(+)	(+)	(-)	(-)
Marginal Solvency Lag	(+)	(+)	(-)	(-)

The variables listed in Table 8 were then analyzed for statistical significance and variables of significance were further reviewed. Age was expected to be positive for the Favorable and the Marginal Income categories following the assumption that older producers were likely to have had the time to lower their debt over the many years that they had been operating. The percentage of owned acres instead of rented acres was expected to be positive for the Favorable and the Marginal Solvency categories. The percentage of acres designated to either: corn, wheat, or soybean acres were seen as having positive expected signs for Favorable and Marginal Solvency category and negative signs for Marginal Income and Vulnerable financial categories because it was assumed that the optimal crop choice would not be specific to one crop due to the climatic variance across the state of Kansas. Gross profit margin was expected to have a positive sign for the Favorable and Marginal Solvency categories and negative signs for the Marginal Income and Vulnerable categories because any time a farm is able to increase their revenue and maintain or lower their production expenses the likelihood of yielding a positive net farm income will increase. Farm size was expected to have a positive impact on farms in the Favorable category due to the assumptions of economies of scale and their ability to operate at a higher level of efficiency. Favorable Lag, Marginal Income Lag, and Marginal Solvency Lag were expected to have positive signs for Favorable and Marginal Income categories and negative signs for the Marginal Solvency and Vulnerable categories. The logic for this assumption was based upon farms attempting to improve both their D/A ratio and their net farm income, but due to the unstable nature of net farm income farms were still more likely to be in the Favorable and Marginal Income categories.

Chapter 5 - Results

The results indicate that some farms do have persistence within a specific financial category. They have characteristics of significance identified by the MNL. The following chapter details the outcome.

5.1 Analysis and Results

Some Kansas farms consistently outperformed their peers due to an unknown management, geographical, or structural advantage. Despite farmers being exposed to many uncontrollable variables farms were able to exhibit financial persistence within the Favorable and Marginal Income categories.

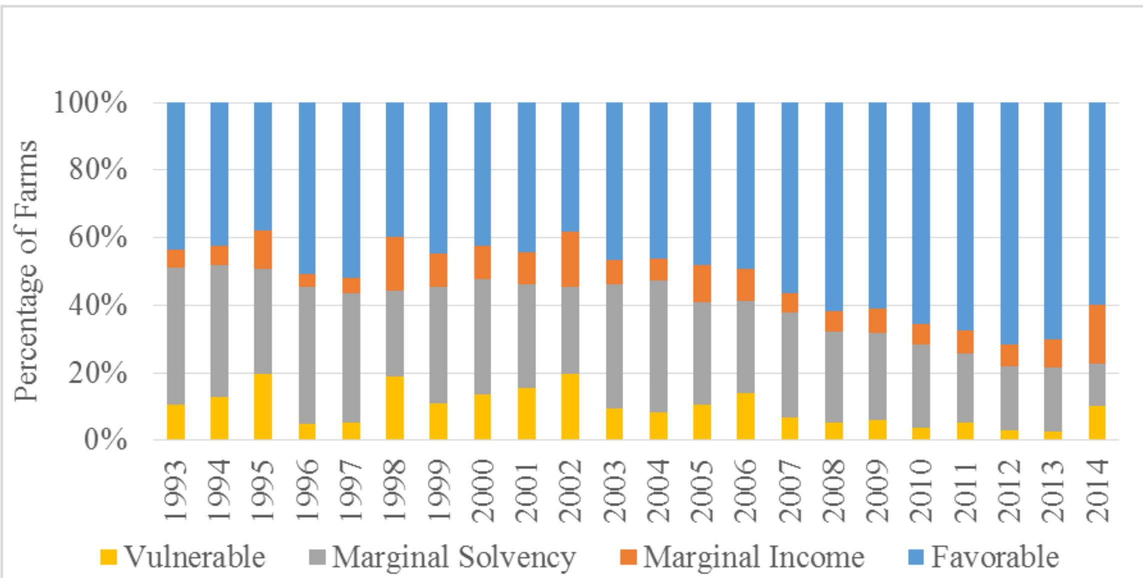

Figure 9. KFMA Annual Financial Category Distribution (1993-2014)

Figure 9 graphically presents the proportion of farms in each financial category for each year. Key events such as the spike in farms with positive NFI acre^{-1} during 1995 and 1996 can be observed. Following the commodity price boom in 2007 farms begin to transition to the Favorable category leaving the Marginal Income category and a large percentage moved from the Vulnerable category to the Marginal Solvency category. During the softening of the commodity market in 2014, the inverse occurred and a large portion of farms entered the Marginal Income category and the Vulnerable category with negative NFI acre^{-1} (Figure 9).

5.2 KFMA Transition Probabilities

The transition probability matrix (Table 9) represents the unbalanced data set. These were estimated to further investigate the types of farms in the four financial categories. The matrix table can be read as the probability of transitioning from category i to category j, rows being i, current state and the columns being j, future state. The primary goal of the first iteration was to search for financial persistence.

Table 9 Unbalanced Markov Chain Probabilities (1993-2014)

	Favorable	Marginal Income	Marginal Solvency	Vulnerable
Favorable	0.83	0.11	0.05	0.01
Marginal Income	0.64	0.28	0.04	0.04
Marginal Solvency	0.12	0.01	0.69	0.17
Vulnerable	0.09	0.03	0.55	0.33

N = 2,397

Table 9 presents the estimated probabilities for a farm to exhibit financial persistence in the current category or to transition to another financial category, i.e. transition probabilities. For example, a farm classified in the Vulnerable category, has a 33% likelihood to remain in that category. The diagonal can be interpreted as the probability of farm financial persistence. The diagonal of probabilities indicates that farms in the Favorable category and the Marginal Solvency are more likely to remain in their current financial categories than transition to another financial category. Farms in the Favorable (financially favorable with positive NFI $acre^{-1}$ and D/A below 0.4) had the highest probability (83%) indicating that Favorable farms are the most stable. Close inspection of the probabilities along the diagonal shows that Favorable farms and Marginal Solvency farms hold similar probabilities, but Marginal Income and Vulnerable farms are not stable. Farms in the Vulnerable and Marginal Income categories are likely to transition away from their current financial categories into another category.

Significant information can be drawn from the transition probabilities. Farms in the Favorable category are stable in their current category indicating that top performing farms are able to overcome uncontrollable variables. It can also be concluded that the largest probability (12%) of leaving the Favorable category is to move to the Marginal Income category. This would suggest that D/A ratio is likely to be constant or vary only slightly from year to year, but profitability can fluctuate more easily relative to D/A, on an annual basis. The probability of a financially Favorable farm incurring large amounts of debt and losing profitability and going to the Vulnerable category is 1%. Farms in the Marginal Income category have a large probability of 64% of improving their profitability. The Marginal Solvency and Vulnerable categories are likewise related. The probability of moving from the Vulnerable category by changing NFI $acre^{-1}$ from negative to positive is 55%. A key result is that farms are more likely to leave a category with negative NFI $acre^{-1}$ then they are to remain. There is a 9% chance that farms will transition to the Favorable category from the Vulnerable category. Further research is needed to create an explanation for this transition. All probabilities do point towards the importance and the long-term challenge that debt creates when determining a farm's financial category.

5.3 Establishing Model Robustness

The results for this research were achieved by using two different statistical tools, Markov Chain probabilities and a multinomial logit model (MNL). The transition probabilities estimated for the smaller, balanced data set used for the MNL yielded similar values when compared to the unbalanced data set. Both the 22-year long and the 15-year long KFMA samples generated similar transition probabilities, plus or minus 6%. Categorical relationships and transition trends were also maintained. The same conclusions that were drawn from the unbalanced data set can be drawn from the balanced results. In a rudimentary method the robustness of the model was confirmed through the second iteration of the Markov Chain probabilities. This second probability matrix ensures that there is a link between the larger unbalanced data set probabilities and the independent variable coefficients and their associated marginal effects calculated using a smaller balanced data set in the multinomial logit model. By comparing Table 9 and Table 10 it is shown that adjusting the sample size and time frame does not substantially affect the results suggesting that the model is robust.

Table 10 Balanced Markov Chain Probabilities (2000-2014)

	Favorable	Marginal Income	Marginal Solvency	Vulnerable
Favorable	0.86	0.07	0.06	0.01
Marginal Income	0.63	0.26	0.08	0.04
Marginal Solvency	0.16	0.01	0.70	0.12
Vulnerable	0.05	0.03	0.61	0.31

N = 260

5.4 Multinomial Logit Model

Due to the structure of the MNL, estimated coefficients were in a form that did not provide values that were immediately interpretable. In order to correct for this issue an additional step is taken to calculate the partial effects of each independent variable. The coefficients are summarized in Table 13. The 15 independent variables along with a constant have decent explanatory power of each financial category with a Pseudo R-squared value of 0.68. Attempting to discern anything beyond the quality of the model requires analysis of the partial effects in Table 11.

Table 11 Multinomial Logit Estimates and Statistics

	Favorable	Marginal Income	Marginal Solvency

Constant.	-1.27796 (3.88776)	2.88033*** (.59142)	.54837 (3.88354)
AGE	.02558 (.06265)	-.00492 (.00604)	.02849 (.06228)
PERCOWN	5.20210** (2.64025)	.62590** (.28641)	2.58020 (2.66257)
PERCCORN	.40946 (4.45747)	.01615 (.55500)	.83141 (4.45284)
PERCWHT	-1.26581 (3.43572)	.15382 (.55062)	-1.87526 (3.42839)
PERCSOY	-2.16834 (3.93434)	.02508 (.56139)	-.40245 (3.93426)
KFMA1	1.34741 (1.65967)	.08211 (.21682)	2.32573 (1.68206)
KFMA2	2.32295 (1.81450)	.14756 (.22706)	3.09496* (1.83333)
KFMA3	1.05105 (3.14874)	.40172 (.36616)	2.48237 (3.12539)
KFMA4	.27117 (1.61509)	-.21803 (.18183)	.24401 (1.60346)
KFMA5	.70665 (2.99346)	-.74401 (.48062)	.20567 (3.07272)
GROSSMAR	-414.858*** (79.44995)	-.75777* (.44043)	-419.014*** (79.45022)
SIZE	-.00123 (.00163)	-.00067*** (.00016)	-.00059 (.00162)
FAVORABLE LAG	-1.89280 (1.80611)	-4.95778*** (.32232)	-6.91038*** (1.78533)
MARGINAL INCOME LAG	-1.17639 (2.21378)	-4.80319*** (.41332)	-6.01967*** (2.21323)
MARGINAL SOLVENCY LAG	-1.58937 (2.21378)	-.85906*** (.31941)	-2.11046 (1.63853)

Multinomial Logit Model	
Log likelihood function	-1240.72
Restricted log likelihood	-3939.97
Chi squared [45 d.f.]	5398.49
Significance level	.00
McFadden Pseudo R-squared	.68
Estimation based on N = 260, K = 48	

Table 12 Estimated Sign Relative to Financial Category

Variable	Favorable	Marginal Income	Marginal Solvency	Vulnerable
Age	(+)	(-)	(-)	(+)
% Owned	(-)	(-)	(+)	(-)
% Corn	(-)	(-)	(+)	(+)
% Wheat	(-)	(+)	(+)	
% Soybean	(-)	(-)	(+)	(+)
Gross Profit Margin	(+)	(-)	(+)	(-)
Farm Size	(+)	(-)	(-)	(+)
Favorable Lag	(+)	(+)	(-)	(-)
Marginal Income Lag	(+)	(+)	(-)	(-)
Marginal Solvency Lag	(+)	(+)	(-)	(-)

The partial effects of statistically significant variables from the MNL related to the Favorable category shown in Table 13 imply that farms with more rented ground, improved marketing and cost management techniques (related to GPM), and that were previously either in the Favorable category or the Marginal Income category are more likely to be in the Favorable category relative to being in the Vulnerable category. Decreasing owned ground by 10% will yield a 0.52% increase in the probability of a farm being in the Favorable category. By improving marketing and lowering input costs, thereby increasing GPM, has the largest impact upon farms in the Favorable category. A 1% increase in GPM yields a 4.3% increase in the likelihood of being from the Favorable category relative to being in Vulnerable category. Favorable Lag, Marginal Income Lag, and Marginal Solvency Lag more or less confirm the conclusions drawn from the Markov Chain probabilities further strengthening their validity. Age, percentage of corn, percentage of wheat, and percentage of soybean are statistically insignificant.

Table 13 Estimated Marginal/Partial Effects for Multinomial Logit

Variable/Financial Category	Favorable	Marginal Income	Marginal Solvency	Vulnerable
AGE	0.00035	-0.00001	-0.00041	0.00006
	(0.00047)	(0.00019)	(0.00047)	(0.00019)
* PERCOWN	-0.05197	0.03250	0.04539	-0.02592
	(0.022)	(0.0078)	(0.022)	(0.0079)
PERCCORN	-0.00167	-0.00411	0.00054	0.00524
	(0.043)	(0.015)	(0.043)	(0.015)
PERCWHT	-0.01047	0.00528	0.01352	-0.00833
	(0.042)	(0.013)	(0.042)	(0.013)
PERCSOY	-0.00024	-0.02074	0.00263	0.01836
	(0.043)	(0.014)	(0.043)	(0.015)
* GROSSMAR	0.43478	-0.33641	0.33417	-0.43254
	(0.047)	(0.044)	(0.047)	(0.040)
* SIZE	0.00005	-0.00001	-0.00005	0.00001
	(0.00001)	(0.0000)	(0.00001)	(0.0000)
* FAVORABLE LAG	0.68851 (0.019)	0.08470 (0.0046)	-0.68532 (0.019)	-0.08789 (0.00040)
* MARGINAL INCOME LAG	0.30387 (0.0087)	0.05984 (0.0055)	-0.30163 (0.0076)	-0.06207 (0.0037)
MARGINAL SOLVENCY LAG	0.05084 (0.014)	0.00350 (0.0049)	-0.04810 (0.013)	-0.00624 (0.0046)

The partial effects of statistically significant variables from the MNL related to the Marginal Income category shown in Table 13 imply that farms with more owned ground, poor marketing and cost management techniques (GPM), and its previous category only has marginal impact upon determining the probability of being in the Marginal Income category. Decreasing rented ground by 10% will yield a 0.33% increase in the probability of a farm being from the Marginal Income Category. By improving marketing and lowering input costs, thereby increasing GPM, farms decrease the probability of being in the Marginal Income category. A 1% increase in GPM yields a 3.3% decrease in the likelihood of being from the Marginal Income category. Favorable Lag and Marginal Income Lag suggests that farms that were previously in the Favorable or Marginal Income categories are 8% more likely to be in the Marginal Income category. Age, percentage of corn, percentage of wheat, percentage of soybean, and Marginal Solvency Lag are statistically insignificant.

The statistically significant partial effects from the MNL related to the Marginal Solvency category shown in Table 13 imply that farms with less rented ground, improved marketing and cost management techniques, and that were previously not in either the Favorable category or the Marginal Income category are more likely to be in the Marginal Solvency category relative to being in the Vulnerable category. Increasing owned ground by 10% will yield a 0.45% increase in the probability of a farm being from the Marginal Solvency Category. This shows that farms with large D/A ratios will likely own their own ground. To maintain a positive NFI acre^{-1} improving marketing and lowering input costs, thereby increasing GPM, has the largest impact upon farms in the Marginal Solvency category. The large negative values of -68% and -30% from Favorable Lag and Marginal Income Lag respectively confirm the assumption that farms in the Marginal Solvency category are unlikely to have been previously in the Favorable or the Marginal Income category. Age, percentage of corn, percentage of wheat, and percentage of soybean are statistically insignificant.

The statistically significant partial effects from the MNL related to the Vulnerable category shown in Table 13 imply that farms with more owned ground, poor marketing and cost management techniques, and that were previously not in any of the other three financial categories are more likely to be in the Vulnerable category. Increasing owned ground by 10% will yield a 0.25% decrease in the probability of a farm being from the Vulnerable. Due to the increased D/A ratio of these farms and their negative NFI acre^{-1}, increasing loan payments while simultaneously having negative profitability will only further increase the probability of Vulnerable farms remaining in the Vulnerable category. Gross profit margin, like the previous three outcomes, has a large impact on the farms in this category. A 1% increase in GPM yields a 4.3% decrease in the likelihood of being from the Vulnerable category. Favorable Lag and Marginal Income Lag show that being from those categories in the previous year lowers the probability of being the Vulnerable category. Age, percentage of corn, percentage of wheat, percentage of soybean, and Marginal Solvency Lag are statistically insignificant.

Chapter 6 - Conclusion

In order for Kansas farms to face the current agricultural headwinds they will need to look towards the top performing farms. These will provide invaluable insights into management and structural characteristics of successful enterprises. If a producer is going to maintain or improve their financial category, then focusing on the correct area of the operation will be the difference between success and failure.

6.1 Agricultural Implications

Kansas is entering a turbulent time in the agricultural industry. Crop prices are projected to remain at or below the current low levels (Kaufman, 2016). Input expenses of seed, fertilizer, pesticides, and equipment are not expected to weaken enough to compensate for these lower crop prices (Kaufman, 2016). Current trends within the financial sector indicate that interest rates will increase, ending near 0% interest rates that have become the norm. With these settings in mind, the agricultural industry, and more importantly the foundation of this industry (the farmers), are going to be tested. The ability to see weaknesses or advantages of specific farms provides valuable information. In estimating farm financial persistence and then analyzing the characteristics, good or bad, this research could be valuable for agricultural lenders and farmers. The implications of the results are twofold. Lenders have a secondary or tertiary method for identifying financial persistence and farmers can focus on key characteristics to change and improve their financial category or maintain their current one.

From the transition probabilities estimated, agricultural lenders will be able to utilize another tool to evaluate the quality of their loan applicant. The persistence or lack thereof exhibited by the four categories provide information into predicting loan applicant future financial persistence. If for instance the loan applicant is in the Marginal Income category, (D/A < 0.4), but they currently are not profitable (NFI $acre^{-1} < \$0$) a lender could be inclined to deny their loan application citing a high probability of default. In this case the agriculture lender has missed an opportunity to generate a new loan for the bank. However, the probability of a farm staying in the Marginal Income category the following year is 28% and the probability of transitioning to the Favorable category is 64%, which means that even though this farm appears to have poor profitability this year, it is much more probable that they will have a positive NFI $acre^{-1}$ the following year. But to compare a second scenario if a farm has fallen into the Vulnerable category, highly leveraged (D/A > 0.4) and are currently unprofitable (NFI $acre^{-1} < \$0$), then the probability of improving their financial category is small. They have a 55% probability of moving to the Marginal Solvency category. A simple switch of their NFI $acre^{-1}$ from negative to positive causes this large probability. The key point is that the probability of improving their D/A ratio and changing their profitability is only 9%. This farm is likely to persist in the Marginal Solvency and Vulnerable categories, making them a higher risk of default. These Markov Chain probabilities are not recommended as an alternative method to estimate loan applicant's quality. The intent of this research was to simply provide agricultural lenders with an additional tool that is able to capture different information and improve the chances of making safe loans.

Farmers will also be able to garner information from the Markov Chain probabilities. Within the probabilities is a farm's potential challenge to take corrective measures and move into the Favorable category. For example, the results indicated that farms that were in the Favorable category had a mixture of rented and owned ground.

Farms could look into supplementing their debt laden purchases with short term rental properties. By quantifying the transition probabilities, a farmer will be able to realistically assess their chances of changing their financial category in the subsequent year. Farmers are encouraged to formulate long-term business plans, but often times they don't. These transition probabilities should help explain to farmers that improving their financial category is not a one-year process, therefore a farmer will need to lengthen their farm plan beyond a single year if farmers are too be successful in transitioning to another category. Coupled with the conclusion that some farms are stable and outperform their peers on an annual basis; the multinomial logit model provided important statistical information on the impact of specific farm characteristics.

The ability to overcome uncontrollable factors is something that most farmers would readily like to learn. To achieve results that added some intuitive values to this research that could provide insights into why farms were able to persist in their category, a multinomial logit model was applied to a continuous set of KFMA farms from 2000 to 2014. Crop mixture and Age were shown to have no impact a farm's financial category. This surprising results would imply that experience and crop choice are irrelevant when determining profitability and D/A ratios. Instead there is the potential that due to the sample and regional bias no correlation could be found between the factors because on a statewide basis some crops fit the optimal acreage allocation better than others. Soybean in the semi-arid South West association would be a poor choice to improve a farms NFI acre^{-1}, and wheat in the North East association, despite being one of the highest performing crop in the South West region would be a poor choice. Age as well is difficult to explain. Age is often used as a proxy for experience, but this variable does not account for alternative sources of knowledge and experience that could be influencing a farms financial category. If farmers are interested in improving their financial category the primary variable to focus on is gross profit margin. It encompasses marketing skills, input cost management, and productivity. Improving any of those areas and consequently increasing a farm's gross profit margin will likely have a positive effect on shifting farms away from less desirable financial categories. Interpreting the percentage of Owned Land variable is not straight forward. Farmers should be cautious in inferring that decreasing the percentage of owned farm land will likely increase their chances of being in the Favorable category. What likely is occurring is that farms with a large share of rented land help lower their D/A ratio by decreasing the required capital, but still allow for positive NFI $acre^{-1}$. Farmers would be wise to supplement the cost of purchasing land with rented land, but this does not imply that farms that own all of their land are financially unstable.

6.2 Further Research Opportunity and Areas of Improvement

In following these results, the next focus of research should be on identifying additional farm characteristics of farms with financial persistence. First and foremost is climate conditions (rainfall, temperature, soil types). The state of Kansas holds several distinct climate ranges; with the semi-arid, warm southwest region with its Ulysses and Richfield silt loams to the wetter northeastern corner of the state with its glacial soils. The variety and range of climates across the state means that a statewide comparison like above should be scrutinized to avoid any spatial bias. Therefore, an additional focus should be paid to the regional associations that KFMA members are in so that they can better be compared to their peers. The second key characteristic believed to play a role in a farm's category is their lifespan. Farms are expected to be at least 3 generations old. A younger farm may be financially stable, but because they carry a larger D/A due to the capital intensive nature of farm ground acquisition, then they may also be more likely to be in the Marginal Solvency category. Considering the long term cropping rotations and cyclical nature of commodity prices reassessing the Markov chain probabilities for each financial category using a 2nd or even 3rd order Markov chain would be beneficial by increasing the time span that impacts the transition probabilities. All of these topics in of themselves would be noteworthy to pursue.

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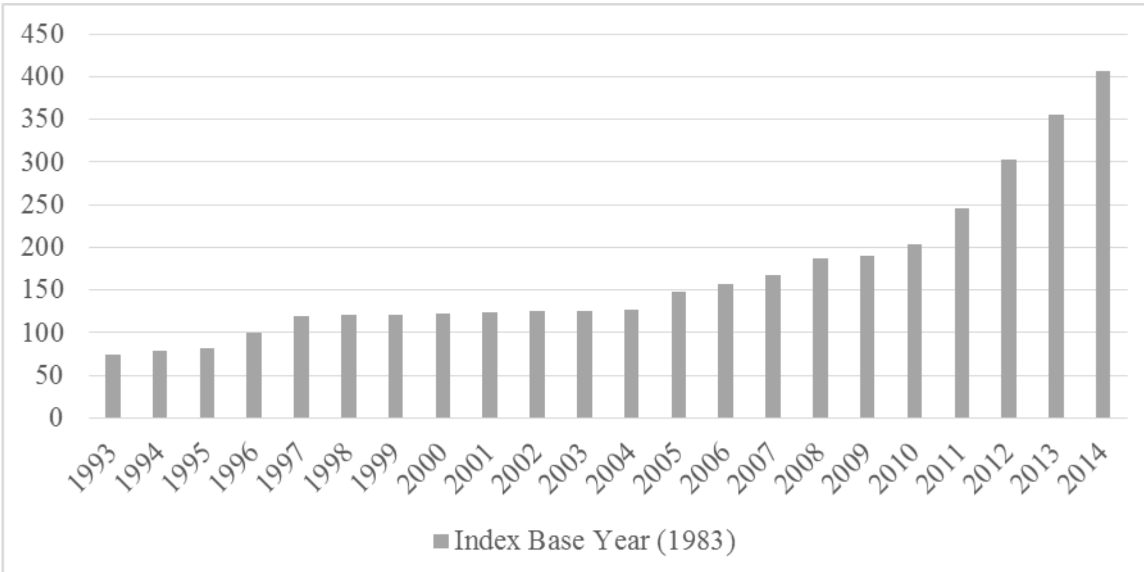
Appendix A - Additional Results

Farmland Index Value (1933-2014)

Figure 9 Annual Kansas Land Index Values



KFMA North Central Region (1) Summary Statistics

Table 10 North Central Region Financial Summary Statistics

Variable	Observations	Mean	Std. Dev.	Min	Max
Gross Profit Margin	4840	.1689343	.3409171	-8.332338	10.05104
Operation Costs	4840	226199.6	226760.8	-15492	3079514
Debt/Asset Ratio	4840	.3837279	.6079897	-.0041164	34.93139
NFI $acre^{-1}$	4840	50.37009	111.0099	-3213.759	2915.529

Table 11 North Central Region Crop Summary Statistics

Variable	Observations	Mean	Std. Dev.	Min	Max
Wheat	4840	.4970844	.4034741	0	4.947166
Corn	4840	.0725779	.1486084	0	1.725264
Grain Sorghum	4840	.2072719	.2168045	0	2.569068
Soybean	4840	.2040048	.2631179	0	2.760807

Table 12 North Central Region Farm Structure Summary Statistics

Variable	Observations	Mean	Std. Dev.	Min	Max
Acres Owned	4840	.3525282	.3091549	0	1
Diversification Ratio	4840	1.399519	.6607937	1	14.94
Total Crop Acres	4840	1212.921	2459.429	0	162271.7

KFMA South Central Region (2) Summary Statistics

Table 13 South Central Region Financial Summary Statistics

Variable	Observations	Mean	Std. Dev.	Min	Max
Gross Profit Margin	5958	.1405626	1.01031	-65.08782	20.2569
Operation Costs	5958	236575.2	243275.3	-260739	2913663
Debt/Asset Ratio	5958	.378007	.9267779	-33.70287	42.56209
NFI $acre^{-1}$	5958	40.11083	73.42566	-1192.222	1746

Table 14 South Central Region Crop Summary Statistics

Variable	Observations	Mean	Std. Dev.	Min	Max
Wheat	5958	.7244307	.5486438	0	4.599039
Corn	5958	.1318497	.2447639	0	3.651297
Grain Sorghum	5958	.2412205	.2818315	0	4.37195
Soybean	5958	.1610721	.3073618	0	8.966955

Table 15 South Central Region Farm Structure Summary Statistics

Variable	Observations	Mean	Std. Dev.	Min	Max
Acres Owned	5958	.2715261	.2977107	0	1
Diversification Ratio	5958	1.171423	.4540154	1	27.25
Total Crop Acres	5958	1468.125	1028.05	8	22474.4

KFMA Southwest Region (3) Summary Statistics

Table 16 Southwest Region Financial Summary Statistics

Variable	Observations	Mean	Std. Dev.	Min	Max
Gross Profit Margin	2338	0.121115	27.10234	-11.866	6.485342
Operation Costs	2338	204382.3	228177.3	2593	2874869
Debt/Asset Ratio	2338	.3059951	.4267406	-.0016466	8.77815
NFI $acre^{-1}$	2338	15.42945	369.3587	-17503.26	1106.7

Table 17 Southwest Region Crop Summary Statistics

Variable	Observations	Mean	Std. Dev.	Min	Max
Wheat	2338	.6981134	.551164	0	4.344861
Corn	2338	.0994219	.2252034	0	2.271854
Grain Sorghum	2338	.2540459	.3481722	0	4.311239
Soybean	2338	.0180757	.0605882	0	.7877041

Table 18 Southwest Region Farm Structure Summary Statistics

Variable	Observations	Mean	Std. Dev.	Min	Max
Acres Owned	2338	.4046766	.3443141	0	1
Diversification Ratio	2338	1.446459	2.867985	1	112.6162
Total Crop Acres	2338	1993.372	1373.362	0	10085

KFMA North East Region (4) Summary Statistics

Table 19 North East Region Financial Summary Statistics

Variable	Observations	Mean	Std. Dev.	Min	Max
Gross Profit Margin	4763	.0842214	6.274346	-194.4347	222.6897
Operation Costs	4,763	236078.6	385025.1	-1.80e+07	2861507
Debt/Asset Ratio	4763	.319072	.8855332	-.0012953	57.65778
NFI $acre^{-1}$	4763	69.86972	246.7824	-1375.623	11030.02

Table 20 North East Region Crop Summary Statistics

Variable	Observations	Mean	Std. Dev.	Min	Max
Wheat	4763	.0896619	.1500656	0	2.284342
Corn	4763	.2981663	.3391855	0	3.362152
Grain Sorghum	4763	.0596989	.1454942	0	5.224784
Soybean	4763	.410253	.3725481	0	3.64073

Table 21 North East Region Farm Structure Summary Statistics

Variable	Observations	Mean	Std. Dev.	Min	Max
Acres Owned	4763	.3615526	.3467947	0	1
Diversification Ratio	4763	1.624061	3.544226	1	141.5
Total Crop Acres	4763	1011.031	775.7599	0	7820

KFMA North West Region (5) Summary Statistics

Table 22 North West Region Financial Summary Statistics

Variable	Observations	Mean	Std. Dev.	Min	Max
Gross Profit Margin	2880	.2049327	1.273062	-26.00841	31.80654
Operation Costs	2880	355475.3	506931.2	3668	5109441
Debt/Asset Ratio	2880	.338223	.4920662	-.6339946	16.34121
NFI $acre^{-1}$	2880	38.38699	221.3101	-11079.05	1203.067

Table 23 North West Region Crop Summary Statistics

Variable	Observations	Mean	Std. Dev.	Min	Max
Wheat	2880	.8030233	.6885691	0	6.003842
Corn	2880	.431354	.6930718	0	5.369645
Grain Sorghum	2880	.2046423	.3767552	0	4.440634
Soybean	2880	.0452721	.1423389	0	2.04707

Table 24 North West Region Farm Structure Summary Statistics

Variable	Observations	Mean	Std. Dev.	Min	Max
Acres Owned	2880	.4195562	.3990447	0	11.31884
Diversification Ratio	2880	1.460132	.989966	1	22.33333
Total Crop Acres	2880	2334.516	1904.23	0	14575.8

KFMA South East Region (6) Summary Statistics

Table 25 South East Region Financial Summary Statistics

Variable	Observations	Mean	Std. Dev.	Min	Max
Gross Profit Margin	7505	.1559939	.6963246	-21.07446	10.6733
Operation Costs	7505	283511.7	384337.1	-97944	6026736
Debt/Asset Ratio	7505	.3815582	.5549284	-.0082574	30.42121
NFI $acre^{-1}$	7505	66.69751	209.0104	-2856.1	11639.26

Table 26 South East Region Crop Summary Statistics

Variable	Observations	Mean	Std. Dev.	Min	Max
Wheat	7505	.2989316	.4117678	0	8.622094
Corn	7505	.2816966	.4439118	0	5.384918
Grain Sorghum	7505	.10616	.1751838	0	3.213256
Soybean	7505	.5577401	.6074215	0	7.127762

Table 27 South East Region Farm Structure Summary Statistics

Variable	Observations	Mean	Std. Dev.	Min	Max
Acres Owned	7505	.376324	.3096326	0	1
Diversification Ratio	7505	1.595984	2.293238	1	95.85714
Total Crop Acres	7505	1278.728	1118.348	0	10511.5

KFMA Statewide Summary Statistics

Table 28 Statewide Financial Summary Statistics

Variable	Observations	Mean	Std. Dev.	Min	Max
Gross Profit Margin	22887	.0914055	8.238734	-1287.866	222.6897
Operation Costs	22887	256678.3	343009.5	-1.80e+07	6026736
Debt/Asset Ratio	22887	.3599607	.7060167	-33.70287	57.65778
NFI $acre^{-1}$	22887	51.73683	203.9905	-17503.26	11639.26

Table 29 Statewide Crop Summary Statistics

Variable	Observations	Mean	Std. Dev.	Min	Max
Wheat	22887	.4715759	.5243046	0	8.622094
Corn	22887	.2173694	.3929537	0	5.384918
Grain Sorghum	22887	.1663363	.2570566	0	5.224784
Soybean	22887	.2919953	.4402402	0	8.966955

Table 30 Statewide Farm Structure Summary Statistics

Variable	Observations	Mean	Std. Dev.	Min	Max
Acres Owned	22887	.354442	.3300732	0	11.31884
Diversification Ratio	22887	1.45142	2.105691	1	141.5
Total Crop Acres	22887	1429.042	1539.283	0	162271.7

Balanced Data Set - Multinomial Summary Statistics

Table 31 Multinomial Logit Financial Summary Statistics

Variable	Observations	Mean	Std. Dev.
Gross Profit Margin	3885	.2042602	.2187898
Operation Costs	3885	312509.9	292315.2
Debt/Asset Ratio	3885	.3365165	.4092307
NFI $acre^{-1}$	3885	64.6706	72.2638

Table 32 Multinomial Logit Crop Summary Statistics

Variable	Observations	Mean	Std. Dev.
Wheat	3885	.3623801	.2690562
Corn	3885	.1875961	.1852694
Grain Sorghum	3885	.1330482	0.1528734
Soybean	3885	0.3169756	0.277196

Table 33 Multinomial Logit Farm Structure Summary Statistics

Variable	Observations	Mean	Std. Dev.
Acres Owned	3885	.3103339	.2779448
Diversification Ratio	3885	1.219711	0.3274133
Total Crop Acres	3885	1562.907	1061.851

Table 34 Number of KFMA Observations by Association

	Association						
	1	2	3	4	5	6	Yearly Total
1993	119	232	101	204	88	273	1017
1994	133	249	98	209	81	294	1064
1995	147	274	111	203	82	289	1106
1996	163	272	103	205	87	327	1157
1997	169	268	87	218	94	319	1155
1998	211	258	128	204	94	326	1221
1999	195	269	106	205	106	293	1174
2000	217	269	119	191	106	311	1213
2001	197	268	105	197	110	302	1179
2002	197	269	102	195	108	302	1173
2003	190	241	118	203	110	291	1153
2004	191	240	109	188	104	296	1128
2005	190	235	73	154	100	288	1040
2006	186	243	70	139	94	272	1004
2007	183	215	65	158	82	267	970
2008	193	209	60	145	94	281	982
2009	194	216	60	140	92	275	977
2010	179	209	55	137	92	275	947
2011	166	189	42	136	83	279	895
2012	154	182	44	134	64	270	848
2013	159	127	42	128	64	252	772
2014	147	131	39	128	63	193	701

Multinomial Logit Model and Partial Effects Statistics

Table 35 Multinomial Logit Model

Multinomial Logit Model	
Dependent variable	Y = Financial Category
Log likelihood function	-1240.72
Restricted log likelihood	-3939.97
Chi squared [45 d.f.]	5398.49
Significance level	.00
McFadden Pseudo R-squared	.68
Estimation based on N = 260, K = 48	

Table 36 Marginal Solvency Category Results

Characteristics in numerator of Prob [Y=1]						
Y = Financial Category	Coefficient	Standard Error	Z	Prob |z|>Z*	95% Confidence Interval	
Constant	-1.27	3.88	-0.33	0.74	-8.90	6.34
AGE	0.03	0.06	0.41	0.68	-0.10	0.15
PERCOWN	5.20**	2.64	1.97	0.05	0.03	10.38
PERCCORN	0.40	4.46	0.09	0.93	-8.32	9.15
PERCWHT	-1.26	3.44	-0.37	0.71	-8.00	5.47
PERCSOY	-2.16	3.93	-0.55	0.58	-9.88	5.54
KFMA1	1.34	1.66	0.81	0.42	-1.90	4.60
KFMA2	2.32	1.81	1.28	0.20	-1.23	5.885
KFMA3	1.05	3.15	0.33	0.74	-5.12	7.22
KFMA4	0.27	1.62	0.17	0.87	-2.90	3.43
KFMA5	0.70	2.99	0.24	0.81	-5.16	6.57
GROSSMAR	-414.85***	79.45	-5.22	0.00	-570.58	-259.14
SIZE	-0.00123	0.002	-0.76	0.45	-0.00442	0.00196
FAVORABLE LAG	-1.89	1.81	-1.05	0.29	-5.43	1.65
MARGINAL INCOME LAG	-1.17	2.21	-0.53	0.59	-5.51	3.16
MARGINAL SOLVENCY LAG	-1.59	1.69	-0.94	0.35	-4.91	1.73

Table 37 Marginal Income Category Results

Characteristics in numerator of Prob [Y=2] Y	Coefficient	Standard Error	Z	Prob |z|>Z*	95% Confidence Interval	
Constant	2.88***	0.59	4.87	0.00	1.72	4.04
AGE	-0.005	0.00604	-0.81	0.42	-0.02	0.00692
PERCOWN	0.63**	0.29	2.19	0.03	0.06454	1.19
PERCCORN	0.016	0.56	0.03	0.98	-1.07	1.10
PERCWHT	0.15	0.55	0.28	0.78	-0.93	1.23
PERCSOY	0.03	0.56	0.04	0.96	-1.08	1.13
KFMA1	0.082	0.22	0.38	0.70	-0.34	0.51
KFMA2	0.15	0.23	0.65	0.52	-0.30	0.59
KFMA3	0.40	0.37	1.10	0.27	-0.32	1.12
KFMA4	-0.22	0.18	-1.20	0.23	-0.57	0.14
KFMA5	-0.74	0.48	-1.55	0.12	-1.69	0.20
GROSSMAR	-0.76*	0.44	-1.72	0.09	-1.62	0.11
SIZE	-0.00067***	0.00016	-4.29	0.00	-0.00097	-0.00036
FAVORABLE LAG	-4.96***	0.32	-15.38	0.00	-5.59	-4.33
MARGINAL INCOME LAG	-4.80***	0.41	-11.62	0.00	-5.61	-3.99
MARGINAL SOLVENCY LAG	-.86***	0.32	-2.69	0.0072	-1.49	-0.23

Table 38 Vulnerable Category Results

Characteristics in numerator of Prob [Y=3]						
Y	Coefficient	Standard Error	Z	Prob |z|>Z*	95% Confidence Interval	
Constant	0.56	3.88	0.14	0.89	-7.06	8.16
AGE	0.03	0.06	0.46	0.65	-0.09	0.15
PERCOWN	2.58	2.66	0.97	0.33	-2.64	7.80
PERCCORN	0.83	4.45	0.19	0.85	-7.90	9.56
PERCWHT	-1.88	3.43	-0.55	0.58	-8.59	4.84
PERCSOY	-0.40	3.93	-0.10	0.92	-8.11	7.31
KFMA1	2.33	1.68	1.38	0.17	-0.97	5.62
KFMA2	3.10*	1.83	1.69	0.09	-0.50	6.69
KFMA3	2.48	3.12	0.79	0.43	-3.64	8.61
KFMA4	0.24	1.60	0.15	0.88	-2.90	3.39
KFMA5	0.21	3.07	0.07	0.95	-5.82	6.23
GROSSMAR	-419.01***	79.45	-5.27	0.00	-574.73	-263.30
SIZE	-0.00059	0.00162	-0.36	0.72	-0.00377	0.00259
FAVORABLE LAG	-6.91***	1.79	-3.87	0.0001	-10.41	-3.41
MARGINAL INCOME LAG	-6.02***	2.21	-2.72	0.0065	-10.36	-1.68
MARGINAL SOLVENCY LAG	-2.11	1.64	-1.29	0.20	-5.32	1.10

Table 39 Partial Effects for Multinomial Logit (Favorable Category) Y=0

(Delta method)	Partial Effect	Standard Error	|t|	95% Confidence Interval	
AGE	0.00035	0.00047	0.75	-0.00056	0.00127
PERCOWN	-0.05	0.02	2.35	-0.10	-0.01
PERCCORN	-0.00167	0.04	0.04	-0.09	0.08
PERCWHT	-0.01	0.04	0.25	-0.09	0.07
PERCSOY	-0.00024	0.04	0.01	-0.08	0.08
GROSSMAR	0.43	0.05	9.16	0.34	0.53
SIZE	0.00005	0.00001	4.30	0.00003	0.00008
FAVORABLE LAG	0.69	0.02	35.26	0.65	0.73
MARGINAL INCOME LAG	0.30	0.00869	34.98	0.29	0.32
MARGINAL SOLVENCY LAG	0.05	0.01	3.73	0.02	0.08

Table 40 Partial Effects for Multinomial Logit (Marginal Solvency Category) Y=1

(Delta method)	Partial Effect	Standard Error	|t|	95% Confidence Interval	
AGE	-0.00001	0.00019	0.03	-0.00038	0.00036
PERCOWN	0.03	0.01	4.17	0.02	0.05
PERCCORN	-0.00411	0.02	0.27	-0.03	0.03
PERCWHT	0.00528	0.01	0.41	-0.02	0.03
PERCSOY	-0.02	0.01	1.43	-0.05	0.01
GROSSMAR	-0.34	0.04	7.66	-0.42	-0.25
SIZE	-0.00001	0.00000	2.09	-0.00002	0.00
FAVORABLE LAG	0.08	0.00457	18.55	0.08	0.09
MARGINAL INCOME LAG	0.06	0.00547	10.95	0.05	0.07
MARGINAL SOLVENCY LAG	0.00350	0.00493	0.71	-0.00616	0.01

Table 41 Partial Effects for Multinomial Logit (Marginal Income Category) Y=2

(Delta method)	Partial Effect	Standard Error	|t|	95% Confidence Interval	
AGE	-0.00041	0.00047	0.87	-0.00132	0.00051
PERCOWN	0.05	0.02	2.05	0.00204	0.10
PERCCORN	0.00054	0.04	0.01	-0.08322	0.08
PERCWHT	0.01	0.04	0.32	-0.07	0.10
PERCSOY	0.00263	0.04	0.06	-0.08	0.09
GROSSMAR	0.33	0.05	7.06	0.24	0.43
SIZE	-.000005	0.00001	4.22	-0.00007	-0.00003
FAVORABLE LAG	-0.69	0.02	35.61	-0.72	-0.65
MARGINAL INCOME LAG	-0.30	0.00759	39.72	-0.32	-0.29
MARGINAL SOLVENCY LAG	-0.05	0.01	3.60	-0.07	-0.02

Table 42 Partials Effects for Multinomial Logit (Vulnerable Category) Y=3

(Delta method)	Partial Effect	Standard Error	|t|	95% Confidence Interval	
AGE	0.00006	0.00019	0.33	-0.0003	0.00043
PERCOWN	-0.03	0.0079	3.28	-0.04	-0.01
PERCCORN	0.00524	0.02	00.35	-0.02	0.04
PERCWHT	-0.01	0.01	0.65	-0.03	0.02
PERCSOY	0.02	0.014	1.27	-0.01	0.047
GROSSMAR	-0.43	0.04	10.70	-0.51	-0.35
SIZE	0.00001	0.00	1.84	0.00	0.00001
FAVORABLE LAG	-0.09	0.00407	21.59	-0.10	-0.08
MARGINAL INCOME LAG	-0.06	.000373	16.65	-0.07	-0.05
MARGINAL SOLVENCY LAG	-0.00624	0.00459	1.36	-0.02	0.00276

Table 44 Financial Category Summary Statistics From 1993-2014

Variables	Favorable	Marginal Income	Marginal Solvency	Vulnerable
Operator Age (Years)	57.58	58.8	55.9	55
Percentage Owned	0.32	0.37	0.26	0.27
Percentage Wheat	0.4	0.42	0.41	0.42
Percentage of Corn	0.19	0.18	0.18	0.17
Percentage of Soybean	0.27	0.26	0.27	0.25
Gross Profit Margin	0.27	-0.16	0.23	-0.19
Farm Size (Acres)	1565.64	1140.96	1510.58	1370.33

R Code for Estimating Markov Chain Probabilities

```
myDf<-read.csv("dat4R.csv")
library(reshape2)
library(markovchain)

test<-dim(myDf)[2]
head(myDf)
dim(myDf)
myDf<-myDf[,2:test]
myDf1<-t(myDf)
kfma41<-melt(myDf1)
dim(kfma41)
head(kfma41)
kfma41.MC<-markovchainFit(data=kfma41$value, byrow=TRUE)
kfma41seqmatrix<-createSequenceMatrix(kfma41[,3], sanitize=FALSE)
sum(kfma41seqmatrix)
#####
# Function to calculate first-order Markov transition matrix.
# Each *row* corresponds to a single run of the Markov chain
trans.matrix <- function(X, prob=T)
{
  tt <- table( c(X[,-ncol(X)]), c(X[,-1]) )
  if(prob) tt <- tt / rowSums(tt)
  tt
}
MC41<-trans.matrix(as.matrix(myDf))
head(MC41)
MC41<-round(MC41,2)
MC41
write.csv(MC41, "MC41test.csv")

myDf1<-t(myDf)
kfma41<-melt(myDf1)
dim(kfma41)
head(kfma41)
kfma41.MC<-markovchainFit(data=kfma41$value, byrow=TRUE)
kfma41seqmatrix<-createSequenceMatrix(kfma41[,3], sanitize=FALSE)
sum(kfma41seqmatrix)

MC41<-trans.matrix(as.matrix(myDf))
MC41<-round(MC41,2)
MC41
write.csv(MC41, "MC41.csv")
```

N-Logit Code for Estimating Multinomial Regression Analysis and Partial Effects

```
|-> Import "mult_data.csv" using Project Tab and Import Data
    create          ;lag1 = (lagged=1)
                    ;lag2 = (lagged=2)
                    ;lag3 = (lagged=3)
                    ;lag4 = (lagged=4)
                    ;y=dependen-1$
Last observation read from data file was       1
End of data listing in edit window was reached
Error    624: No valid data found in sample=1 to  2222
|-> IMPORT;FILE="H:\mult_data.csv"$
Last observation read from data file was    3885
|-> create          ;lag1 = (lagged=1)
|-> ;lag2 = (lagged=2)
                    ;lag3 = (lagged=3)
                    ;lag4 = (lagged=4)
                    ;y=dependen-1$
Error      1: Unrecognized command.  (Missing ; ?)
|-> create          ;lag1 = (lagged=1)
                    ;lag2 = (lagged=2)
                    ;lag3 = (lagged=3)
                    ;lag4 = (lagged=4)
                    ;y=dependen-1$
|-> mlogit          ;lhs = y
                    ;rhs = one, age, diverse, irr, percown, perccorn, percwht, percsorg,
percsoy, perret, costs, size, lag2, lag3, lag4
                    ;alg = bfgs
                    ;maxit = 1000
                    ;tlg = 1e-9$
```