

**Evaluation of Farm Credit Express  
Delinquencies**

by

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B.S., The Pennsylvania State University, 2010

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A THESIS

Submitted in partial fulfillment of the requirements

for the degree

**MASTER OF AGRIBUSINESS**

Department of Agricultural Economics

College of Agriculture

**KANSAS STATE UNIVERSITY**

Manhattan, Kansas

2018

Approved by:

Major Professor  
Dr. Christine Wilson

## **ABSTRACT**

Credit scoring is a tool used to make lending decisions. AgChoice Farm Credit has a dealer financing program called Farm Credit Express that makes lending decisions based on a scoring model. Farm Credit Express is a dealer financing option for farm equipment purchases. AgChoice has generated significant loan volume with this program but has also experienced challenges with loan delinquencies as field staff must service loans that they did not originate.

This thesis evaluates loan delinquencies within AgChoice Farm Credit's Farm Credit Express ("FCE") program. The thesis develops a regression model that includes delinquencies as the dependent variable and Total AgChoice Borrowing, Original Loan Amount, Farming Segment, CBI Score, AgScore, and FCE Only as the independent variables. The model provides an examination of AgChoice's Farm Credit Express delinquencies and evaluates the variables mentioned above and their ability to predict delinquencies.

The results showed that Total AgChoice Borrowing, Original Loan Amount, CBI Score and FCE only were statistically significant independent variables. Based on results of the model, recommendations were made to potentially reduce future delinquencies in the Farm Credit Express loan portfolio.

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## ACKNOWLEDGMENTS

The author wishes to thank Dr. Christine Wilson for her guidance and suggestions throughout the thesis writing process. Her willingness to be flexible and provide quick response to questions was a great asset. I sincerely appreciate everything she has done to help me accomplish this milestone. I would also like to thank Dr. Allen Featherstone and Dr. Elizabeth Yeager for serving on my thesis committee.

Special thanks to Deborah Kohl and Mary Bowen for everything they do to support the MAB program. I am extremely grateful for my MAB classmates. The camaraderie and new friendships were the best part of this program. I may not have survived without the group texts and snapchats. Thanks for making the distance courses not seem so distant.

Finally, I would like to thank my family and friends for all of their support. Many life changes have happened during the last 2.5 years and to have finished my master's on top of everything else is somewhat of a miracle. It could not have been done without much love and support. Special thanks for Joe for putting up with me when I was stressed and to my parents for believing I can do more than I think I can.

## CHAPTER I: INTRODUCTION

AgChoice Farm Credit (“AgChoice”) is a \$1.8 Billion agricultural lending association and is part of the Farm Credit System, a nationwide lending cooperative. AgChoice offers a comprehensive range of financial services to full-time and part-time farmers in a chartered territory including 52 counties in central, western and northern Pennsylvania along with four counties in West Virginia. AgChoice’s primary focus is loans with the majority of its revenue from interest income. Over the last decade, AgChoice has continued to diversify and offer additional financial services to its customer-owners including consulting, accounting, and record-keeping offerings. AgChoice is continually pursuing ways to improve efficiencies and better serve its customers.

One of the most successful new programs for AgChoice is Farm Credit Express. Several years ago, AgChoice collaborated with Mid-Atlantic Farm Credit, another association within the Farm Credit System, to offer its Farm Credit Express (“FCE”) dealer financing program to AgChoice customer-owners. Farm Credit Express has partnered with over 1,000 equipment dealership locations across the Mid-Atlantic region to offer a Farm Credit dealer financing option. This program is designed to compete with other dealer financing options such as John Deere Financial with quick decisions (goal of 20 minutes), low rates and easy execution. Dealers use the Farm Credit Express Program because it is an alternative financing option with no recourse – meaning that once the loan is booked to AgChoice, the dealership has no requirements in helping to collect the loan. The dealer handles the application that is submitted to Mid-Atlantic for approval and processing. AgChoice employees get an email notification when a FCE loan has been approved for one

of their customers. AgChoice pays Mid-Atlantic a servicing fee and all new loans are booked directly to AgChoice's loan portfolio.

Currently AgChoice's FCE portfolio is \$62 million, which is relatively minor compared to total association loan assets of \$1.8 billion. There have been some obvious benefits to AgChoice with the FCE program. AgChoice is getting loan volume that historically would have likely gone to other trade credit. In addition, there are new customers exposed to AgChoice Farm Credit. FCE is a great tool to get prospects exposed to AgChoice and proceed to develop a larger, long-term lending relationship. AgChoice has also been able to reduce its servicing costs by encouraging customers who are inquiring for small equipment loans to use the FCE program. This reduces the servicing on small loans that are less profitable for the association.

The negative impact of the FCE program is that it appears to branch staff that FCE loans have a higher delinquency rate compared to the rest of AgChoice's portfolio. This puts extra stress and frustration on AgChoice field staff as they are trying to manage delinquencies to borrowers that "they don't even know" or "didn't even make the loan to."

This thesis will compare FCE delinquencies to the entire AgChoice portfolio and evaluate data from the FCE portfolio to determine if there is a correlation between certain variables and FCE delinquencies. From an association level, the benefits of the FCE program outweigh the additional servicing on delinquencies. Over the past two years, managing FCE delinquencies has been particularly difficult for the field staff and that is what prompted this thesis research topic.



## CHAPTER II: LITERATURE REVIEW

When it comes to agriculture financing opportunities, farm equipment is the second largest asset on a producer's balance sheet, following real estate. For the Farm Credit System, equipment financing is a significant portion of its portfolio. Financing for equipment can be provided through direct portfolio lending from individual Farm Credit Associations or through dealer financing programs such as Farm Credit Express (Koenig 2016). When borrowers finance equipment through dealer financing programs, typically that loan decision is made via a credit scoring model.

Credit scoring is a tool lenders use to assess risk in the loan application based on a comprehensive evaluation. A borrower's application information along with information collected from credit reporting agencies are entered into an automated underwriting system. The system evaluates all of this information to determine the probability that this loan will repay as agreed (Federal Reserve Bank of St. Louis 1998). This method generates a "score" that lenders can use to rank borrowers relative to the risk profile of the applicant. Lenders develop a scoring model, or "scorecard," that is built by evaluating historical data on the repayment of existing or formerly made loans to determine which borrower characteristics are valuable in predicting whether the loan paid as agreed (Mester 1997).

Information used in the scoring model is acquired through borrower loan applications and from credit bureau agencies. Many factors including but not limited to borrower's income, current debt levels, years in business, and historical repayment performance may indicate loan repayment and be used in the scorecard process. Regression analysis relating loan performance to collected variables is used to determine the combination of factors that forecast repayment issues and how much weight should be

given to each variable. It is likely that some of the factors the developer of the model begins with will not make it into the final model (Mester 1997).

Fair, Isaac & Co., a leading developer of scoring models, developed one of the most used scoring models. The scores range from 400 to 900 and are known as FICO scores. A higher score indicates less risk for the lender. Fair, Isaac & Co. surveyed one million loan records and found that one in eight borrowers with a FICO score below 600 was either severely delinquent or in default on their loan. On the other hand, if borrowers had a score over 800, only one in 1,300 had similar repayment issues (Federal Reserve Bank of St. Louis 1998). In general when someone references “your score,” they are referring to your FICO score. However, FICO is not the only score used to make lending decisions. Many lenders use their own scores, but often incorporate FICO scores into their scoring model along with other borrower information. In addition, while FICO scores are the most commonly used, there are other credit bureau scores available (Indiana Department of Financial Institutions n.d.).

Most scoring models follow the same logic of the FICO score, higher scores predict a lower risk to the lender. Typically a lending institution sets a cutoff score based on the amount of risk it is willing to carry. Following the model, the lender would approve applicants with scores above cutoff and deny scores below cutoff. Often times, lenders will take a closer look at loan applications that generate a score close to cutoff before approving or denying the loan request. No model is perfect: some accounts that default received higher scores than accounts with no repayment issues (Mester 1997).

Historically in small communities, loans were made based on word of mouth who paid their debts and who did not. As creditors became larger and the number of applications increased, the lending system needed to develop a more systematic and efficient way to make lending decisions (Indiana Department of Financial Institutions n.d.). Credit scoring was first used in the auto loan and consumer credit industries but is now used for all types of lending including residential and business lending (Federal Reserve Bank of St. Louis 1998).

One of the largest benefits to credit scoring is that it greatly reduces the time needed in the loan approval process. Credit scoring can reduce loan analysis time to well under an hour when historically loan applicants could wait up to two weeks to know if their loan was approved or denied. This time savings not only benefits the customer but results in cost savings for the lender as well. Even if a lender does not want to depend solely on credit scoring for loan decisions, scoring can increase lender efficiency by allowing staff to spend more time working with borderline borrowers (Mester 1997).

Credit scoring has also increased objectivity in lending decisions. By using uniform standards when assessing a borrower's credit factors, credit scores help make sure that all applicants are on a level playing field (Federal Reserve Bank of St. Louis 1998). Use of a credit scoring model allows lenders to apply the same underwriting criteria to all applicants regardless of race, gender, or other factors that are illegal from being used in credit decisions (Mester 1997).

The growing use of credit scoring is leading to increased competition in the lending industry, particularly for small-business lending. Historically, lenders to small businesses

have been smaller lending institutions, like community banks, that have a physical branch presence in the community. Credit scoring is changing the way lenders make small-business loans. Large lending institutions have entered the market by using automated and centralized processing of loan applications and now determine lending decisions based on a credit scoring model. Now, large lending institutions are able to generate significant volumes of small-business loans even in areas where they do not have extensive branch networks (Mester 1997).

By utilizing a credit scoring model, the Farm Credit System is able to compete with dealer financing options such as John Deere Financial and CNH Industrial Capital for equipment financing. AgChoice uses a credit scoring model called “AgScore” in all of its loan applications. For Farm Credit Express loans, if the loan amount is under \$250,000, then decision for approval or denial is based only on the AgScore.

## **2.1 Other Research**

There has been significant research completed on agricultural credit scoring models. This thesis will review the results of research conducted by Ellinger, Splett, and Barry. The primary objective of their study was to measure the characteristics and consistency of credit scoring models used by agricultural lenders (Ellinger, Splett and Barry 1992).

Ellinger, Splett and Barry (1992) suggest that credit scoring models vary for three main reasons. First, lenders use credit scoring models for different motives. Some lenders use their credit scoring model along with other financial information to determine loan approval while some lenders rely solely on the model for loan decisions without

considering other financial factors. Models may differ depending if they are used only for loan approval, loan pricing, or a combination of both loan approval and pricing. When using a model to make loan approval decisions, the model focuses on acceptable versus unacceptable loans. There is no varying levels of acceptance. When using a model to make loan pricing decisions, the model focuses on categorizing acceptable loans into groups based on varying levels of risk (Ellinger, Splett and Barry 1992).

The second reason credit scoring models may be different is the varying risk tolerance of lending institutions. A risk-tolerant lender will have more liberal risk classifications while a risk-averse lender will be more conservative. Loan demand and competition may also influence a lender to become more liberal with their credit scoring model (Ellinger, Splett and Barry 1992).

Third, credit scoring models may vary because of specific borrower characteristics and quality of information provided to individual lenders. Certain geographical regions with specific farm types may have models with performance measures and interval ranges that are applicable to specific types of borrowers. In addition, credit scoring models may vary based on lender experience using credit scoring models and the quality of financial data provided by loan applicants. Models may be based on the information producers have available versus the measures that most accurately predict creditworthiness (Ellinger, Splett and Barry 1992).

Credit scoring model results impact borrowers availability and/or cost of financing. Inconsistencies in agricultural credit scoring models would suggest that certain borrowers might have a competitive advantage in obtaining credit. Ellinger, Splett, and Barry (1992)

observed the results of 87 credit scoring models using 324 different loan cases. Two approaches were used to evaluate the consistency between the credit scoring models. The first approach detects the types of loan cases that result in consistent or inconsistent scores. This approach compared the correlation between the varying loan cases. The second approach identifies the credit scoring models that show consistent or inconsistent rank. This approach compares each model's ranking of the 324 loan cases. An equal ranking of the 324 loan cases by the 87 models would indicate model consistency (Ellinger, Splett and Barry 1992).

The first approach resulted in 52,326 unique correlation coefficients. Only 6.5% of the correlations are over 0.90, while 28.56% are below 0.50. This indicates inconsistency in the models. The second approach compares each bank's ranking of the 324 loan cases. The coefficient of concordance for the 87 banks' ranking of the 324 loan cases is 0.87. While the rankings are positively correlated, significant differences exist within the ranks. For example, two bank models ranked a loan case with strong solvency and liquidity but weak profitability and management as 33<sup>rd</sup> and 283<sup>rd</sup> (Ellinger, Splett and Barry 1992).

Ellinger, Splett and Barry's results indicated that there was a need to address the lack of a uniform credit scoring model for agricultural lenders. Improvement has been made across the agricultural lending industry but it is unlikely that individual lenders credit scoring models will be 100% consistent. It is expected that lenders with a higher risk tolerance will have a model that approves a loan for the same borrower that a more conservative lender denies. The Farm Credit Express program this thesis evaluates is a good example.

The credit scoring model for Farm Credit Express loans determines loan approval or denial. Pricing is the same for all loans that are approved. CNH Industrial Capital (“CNH”) has often approved loans that were denied through the Farm Credit Express program but at a significantly higher interest rate than offered through Farm Credit Express. This indicates that CNH’s credit scoring model determines loan approval and loan pricing.

In addition to determining loan approval and loan pricing, credit scoring models can be used to assign probability of default. There has been research completed on probability of default in the Farm Credit System. This thesis will review the results of research by Featherstone, Roessler and Barry as well as Featherstone, Wilson, and Zollinger.

Featherstone, Roessler and Barry (2006) noted that nearly all lenders used some type of risk-rating system. Many systems include two ratings – one for the probability of default (PD) and one for the amount of potential loss given that default occurs. Lenders have their own definitions of risk and risk ratings. The lack of consistency increases the difficulty of uniformly assessing the risk held by agricultural lenders. The objective of Featherstone, Roessler and Barry’s research was to develop a consistent risk-rating system with improved granularity using data from the Seventh Farm Credit District (Featherstone 2006).

Featherstone, Roessler and Barry’s (2006) research utilized historical financial origination ratios based on the lenders current underwriting standards. The ratios included were repayment capacity, solvency, liquidity and collateral. Loans approved using scorecard systems were not included in the data. Given that scorecard-approved loans do

not have traditional origination ratios, they cannot be analyzed in the same model as traditionally approved loans (Featherstone 2006).

Featherstone, Roessler and Barry (2006) classified each loan into ten risk categories. The PD for each loan is determined from an equation derived from binary logit regression models estimated from loan origination data. The models result in a PD assignment for each loan. The loans were then mapped to a similar PD grid of S&P publicly rated firms. This mapping allows lenders to know the characteristics of loans in each risk-rating category that they can then use to develop benchmarks for each risk-rating class (Featherstone 2006).

Results indicated that all of the variables were statistically significant at the 99.99% level. Using a cutoff of 2% for classifying default, the model accurately predicted 65.4% of the loans that would default. Logit results were used to map the loans into ten risk-rating classes based on an adaption of S&P reported probabilities of default for their 17 risk-rating categories. S&P is a model that has been established and validated and provides consistency in the marketplace. Buyers of Farm Credit System loans and other securities will better understand the risk in the portfolio of loans if it is equated to S&P ratings. Based on the model, 35.4% of all loans in the portfolio would be in a S&P class nine and 11.6% in S&P class ten. This is a significant percentage of loans that are expected to enter a problem or adverse risk-rating class. The high percentage of loans in classes nine and ten suggests that the Farm Credit System may want to increase the granularity of their risk ratings or modify the category definitions (Featherstone 2006).



Featherstone, Wilson and Zollinger (2017) focused their research on the migration of accounts across the association's currently established PD rating categories with negative movement being a predecessor to potential loan default. The data consisted of 17,943 observations between 2006 and 2012 and contained various fields of data including balance sheet date, earnings statement date and PD rating as of the statement date. OLS regression was used to evaluate the data to determine how the current period PD rating and component ratios influenced the PD rating one year, three years and five years out. Independent variables are the current PD rating and the following ratios: current ratio, debt to asset ratio, gross profit to total liabilities ratio, the inverse debt coverage ratio, working capital to gross profit and funded debt to EBITDA (A. M. Featherstone 2017).

Results showed that financial ratio information gathered today does forecast PD ratings up to three years in the future. Current ratio information does not forecast five years into the future, therefore there is a need to update financial information on a regular basis. Results indicate that debt to asset information is very important in predicting risk ratings. Given income volatility in the agriculture sector, agricultural lenders need to obtain up-to-date financial information from their borrowers to accurately assess the risk of their portfolio (A. M. Featherstone 2017).

## **2.2 Summary**

Credit scoring has greatly influenced the finance industry by allowing lenders to make fast, objective decisions. Lending institutes developed scorecards which are used to make loan approval, pricing and risk rating decisions. There is room for the agricultural lending industry to have more consistent scorecard and risk rating models.

## CHAPTER III: METHODS

When evaluating delinquencies, there are many factors to consider. This thesis will use regression analysis to evaluate several variables to determine if they impact Farm Credit Express delinquency rates. A logistic regression model will be used because the dependent variable is binary.

### 3.1 Variable Selection

Selecting the variables is the first step to developing a regression model. This thesis is evaluating FCE delinquencies, therefore the dependent variable is whether the loan has been greater than 30 days past due at least once during the last four years. Factors that are expected to predict delinquencies are used as independent variables in the regression analysis. The variables are identified in Table 3.1 and then further described below.

**Table 3.1: Variables Used in Regression Model**

Category	Variable
Dependent	Dummy variable for delinquencies
Independent	Total AgChoice Borrowing Original Loan Amount Dummy Variable for Part Time or Full Time Farmer CBI Score AgScore Dummy Variable for FCE Only Loan

**Dummy Variable for Delinquencies** – 0 represents no delinquencies over 30 days and 1 means that the loan has been over 30 days delinquent at least once during the last four years.

**Original Loan Amount** – amount of loan when it was originated. This variable was chosen because it seems that smaller loans are more delinquent than larger loans.

**Total AgChoice Borrowing** – total dollar value of AgChoice lending exposure to a specific borrower. Often this includes multiple loans. This variable was chosen as it seems borrowers with less exposure to AgChoice are more often delinquent.

**Dummy Variable Farming Segment** – 0 is part time farmer and 1 is full time farmer.

This variable was chosen to determine if a certain segment of our portfolio has more risk than the other. It is expected that full time farmers will be more delinquent than part time farmers considering the volatility in commodity markets.

**CBI Score** – credit bureau score from Experian. This variable was chosen because the CBI score is utilized in the AgScore scoring model for FCE loans. It is expected that borrowers with a higher CBI Score are less likely to be delinquent.

**AgScore** – score from the Fair Isaac Scoring Model developed for Farm Credit Associations. This variable was chosen because a borrower's AgScore determines approval of an FCE loan. Currently, the minimum cutoff score is 160. The variables used by the FCE program to generate an AgScore include borrower's age, CBI score, loan amount, and years in business. It is expected that higher AgScores will predict lower delinquencies.

**Dummy Variable for FCE Only** – 1 are borrowers that only have an FCE loan and 0 are borrowers that have an FCE loan but also have other loans with AgChoice. This variable was chosen to determine if FCE only loans are more likely to be delinquent. It is expected that FCE only loans are more likely to be delinquent.

### 3.2 Regression Model

After the variables are selected, data are collected and the equation is estimated.

Below is the estimated equation:

$$\ln(\rho/(1-\rho)) = B_0 + B_1*TotalAgChoiceBorrowing + B_2*OriginalLoanAmount + B_3*FarmingSegment + B_4*CIBIScore + B_5*AgScore + B_6*FCEOnly$$

*Delinquencies* is a dummy variable where 0 represents no delinquencies over 30 days and 1 represents the loan has been over 30 days delinquent at least once in the last four years. *Total AgChoice Borrowing* is the total dollar value of loans a customer has borrowed from AgChoice. The *Original Loan Amount* is the starting balance of the loan. The *Farming Segment* is a dummy variable where 0 is part time farmer and 1 is full time farmer and the *CBI Score* is a borrower's credit bureau score from Experian. The *AgScore* is a borrower's score from the Fair Isaac Scoring Model. The *FCE Only* is a binary variable where 1 are borrowers with only FCE loans and 0 are borrowers who have an FCE loan but also have other loans with AgChoice.

Once the model has been developed, a computer regression package (Gretl 2017) is used to estimate the equation. Once the analysis has been completed using Gretl, the ability of the independent variables to predict delinquencies is determined.

## CHAPTER IV: DATA

### 4.1 Data

The data for this thesis were collected from AgChoice's existing loan portfolio. The data include the status of 15,640 loans as of January 31, 2018. The loans were originated between February 25, 2011 and January 31, 2018. Of the 15,640 loans, 2,896 or 18.52% were originated through the Farm Credit Express program. Of the 2,896 FCE loans, 1,899 were FCE only loans meaning the borrowers had no other lending relationship with AgChoice outside of FCE.

In the data set, a loan is considered delinquent if it has gone over 30 days past due on the loan system. The data set does not indicate how many times a loan has been over 30 days past due, just that it has been delinquent at least one time. Table 4.1 below shows the number of loans in the data set along with the percent of delinquencies.

**Table 4.1: Summary Loan Delinquencies**

---

Category	Number of Loans	Number of Loans w/delinquencies over 30 days within the past four years	
			% Delinquencies
All Loans	15,640	501	3.20%
Non-FCE Loans	12,744	362	2.84%
FCE Loans	2,896	139	4.80%
FCE Only Loans	1,899	127	6.69%

---

Given the thesis is evaluating FCE delinquencies, only the data for the 2,896 FCE loans were used in the Gretl regression model. Fifty-two loans were removed from the data set because of incomplete information. Table 4.2 provides some key statistics on the 2,844 FCE loans that were used in the Gretl regression model. For the dummy variables, the table shows that 62% of the 2,844 loans are full time farmers and 66% are FCE only loans (no other loans with AgChoice). The dummy variables do not have a minimum, maximum

or a standard deviation. For the Total AgChoice Borrowing variable, the minimum is \$0. It is possible to have a \$0 Total AgChoice Borrowing if the loan is in non-accrual status and has been written off of the loan system. There is one loan with a \$0 Total AgChoice Borrowing in the FCE data set.

Average Total AgChoice Borrowing for borrowers with FCE loans is \$258,490 but the median is only \$34,971 which indicates the majority of our FCE loans are to borrowers with less than \$50,000 of exposure. Average and median CBI Score and AgScore are similar.

**Table 4.2: Summary Statistics of FCE Loans used in Gretl Regression**

<b>Variable</b>	<b>Average</b>	<b>Median</b>	<b>Deviation</b>	<b>Minimum</b>	<b>Maximum</b>
TotalAgChoiceBorrowing	\$258,490	\$39,514	\$569,720	\$0	\$7,978,500
OriginalLoanAmount	\$34,971	\$24,768	\$34,625	\$2,735	\$340,270
FarmingSegment	62%	-	-	-	-
CBIScore	757	762	41	550	844
AgScore	191	194	16	103	238
FCEOnly	66%				

## 4.2 Expected Signs

Table 4.3 outlines the expected signs and descriptions of the regression model equation.

**Table 4.3: Expected Coefficient Signs and Variable Description**

Coefficient	Variable	Expected Sign	Variable Description
$\beta_1$	TotalAgChoiceBorrowing	-	Total AgChoice Borrowing
$\beta_2$	OriginalLoanAmount	-	Original Loan Amount
$\beta_3$	FarmingSegment	+	Dummy Variable for Part Time or Full Time Farmer
$\beta_4$	CBIScore	-	Credit Bureau Score from Experian
$\beta_5$	AgScore	-	Score from Fair Isaac Scoring Model
$\beta_6$	FCEOnly	+	Dummy Variable for Borrowers that have FCE Only Loans

The coefficient  $\beta_1$ , *Total AgChoice Borrowing*, is expected to be negative because as total loan exposure increases it is expected there will be less delinquencies because typically, more analysis is completed and there is more oversight on the account.  $\beta_2$ , the coefficient for *Original Loan Amount*, is expected to be negative with the expectations that borrowers are more likely to pay larger loans on time. For the *Farming Segment*, coefficient  $\beta_3$  is expected to be positive where the dummy variable, 0 is part time farmer and 1 is full-time farmer. The coefficient is expected to be positive because part time farmers typically have off-farm income that provides a more stable income source. It is expected that full-time farmers who have more income volatility due to variability in commodity prices would have more delinquencies.

The coefficient  $\beta_4$ , *CBI Score*, is expected to be negative indicating that individuals with a higher CBI score have a lower risk of delinquencies. *AgScore*, coefficient  $\beta_5$  is also expected to be negative signifying that as a borrower's AgScore increases, the probability of delinquency decreases. Finally, the coefficient  $\beta_6$ , *FCE Only*, is expected to be positive

given that borrowers who have only FCE loans are more likely to be delinquent than borrowers who have an additional lending relationship with AgChoice.

### **4.3 Summary**

The data section summarizes the data collected and utilized in the regression model. It also includes hypotheses for the regression model output by predicting the signs for the coefficient of each variable.



## CHAPTER V: RESULTS

This chapter evaluates the results from the regression model which was described in previous chapters. Table 5.1 shows the regression output. Farm Credit Express loans with a delinquency within the last four years were used as the dependent variable. All of the signs matched the hypothesized signs except for the farming segment coefficient, which is negative, and the original loan amount coefficient, which is positive.

After estimating the model with the proposed variables, it was suspected that the original model may have multicollinearity because *CBI Score* impacts a borrowers *AgScore*. The model was re-run twice, once without *CBI Score* as a variable and once without *AgScore* as a variable. The results were different and confirmed multicollinearity. Therefore, the final model does not include *AgScore* as a variable (Table 5.1).

### 5.1 Regression Results

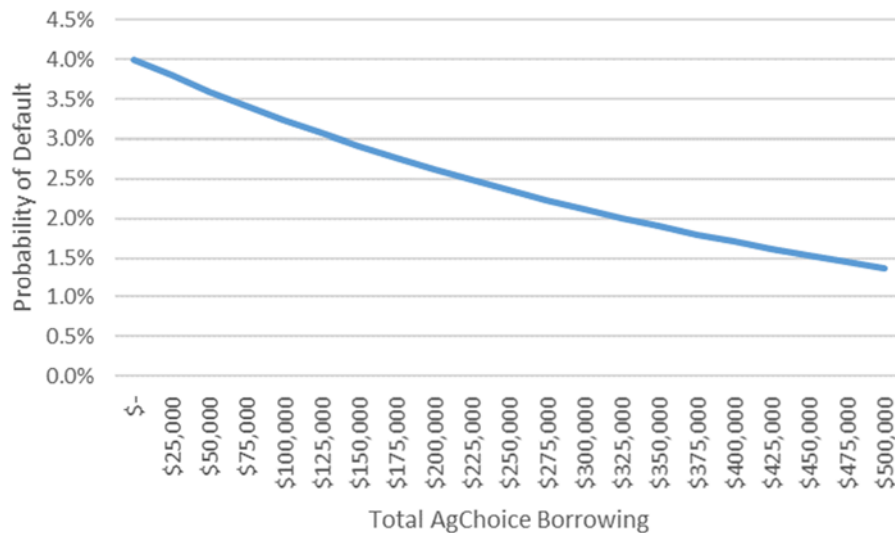
**Table 5.1: Regression Output**

	<b>Coefficient</b>	<b>Std. Error</b>	<b>z</b>	<b>Slope</b>	<b>p-value</b>	
Constant	9.0337	1.58501	5.699	-	<0.0001	***
TotalAgChoiceBorrowing	-2.19E-06	8.46E-07	-2.59	-4.95E-08	0.0096	***
OriginalLoanAmount	8.27E-06	2.72E-06	3.036	1.87E-07	0.0024	***
FarmingSegment	-0.312646	0.192219	-1.627	-7.33E-03	0.1038	
CBIScore	-0.017202	0.00210589	-8.169	-3.89E-04	<0.0001	***
FCEOnly	1.08215	0.33522	3.228	0.0216713	0.0012	***
R-squared		0.12		Adjusted R-squared		0.11

The *Total AgChoice Borrowing* coefficient is negative and indicates that as a borrower's Total AgChoice Borrowing increases, the risk of delinquencies decreases. With a p-value of 0.0096, this variable is statistically significant at the 1% significant level. Slope is the change in probability of the dependent variable when the independent variable

is changed by one unit while holding all other variables at their mean. For every \$10,000 increase in Total AgChoice Borrowing, borrowers are .05% less likely to default. Figure 5.1 shows the change in Probability of Default (chance of delinquencies) as Total AgChoice Borrowing increases while all other variables are held at their mean.

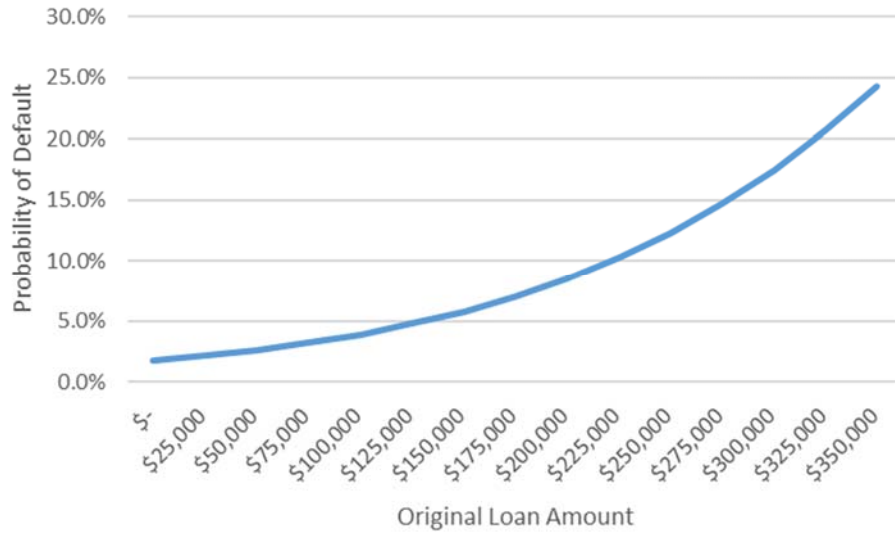
**Figure 5.1: Impact of Total AgChoice Borrowing on Probability of Default**



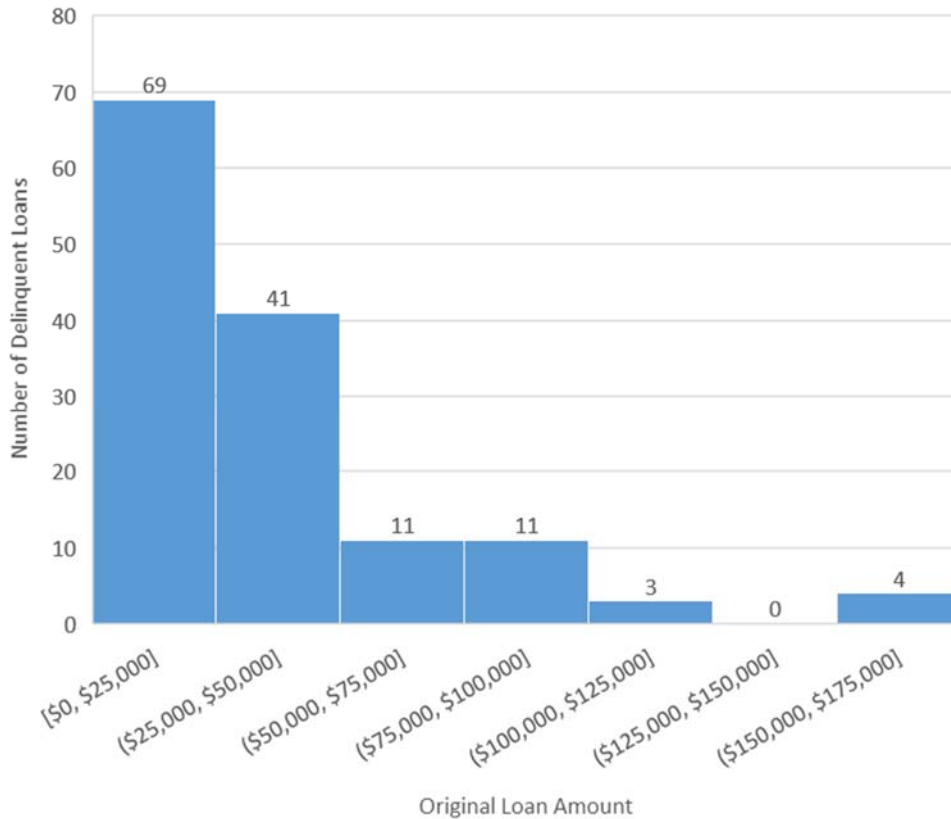
The coefficient for Original Loan Amount is positive, which indicates as loan amounts increase, there is more likely to be a delinquency. Note that this is a different sign than the hypothesis for this coefficient. The positive coefficient for Original Loan Amount can be rationalized that as loan size increases, so does payment size. For loans that are set up on annual payments to match cash flow from the farming operation, it is reasonable that borrowers may default on a larger annual payment versus a smaller payment. Original Loan Amount is statistically significant at the 1% level with a p-value of .0024. For every \$10,000 increase in loan amount borrowers are 0.19% more likely to default. Figure 5.2 shows the change in Probability of Default (chance of delinquencies) as Original Loan Amount increases while all other variables are held at their mean. Figure 5.3 shows the

range of original loan amounts for the 139 delinquent FCE loans. Fifty percent of the delinquencies were under \$25,000.

**Figure 5.2: Impact of Original Loan Amount on Probability of Default**



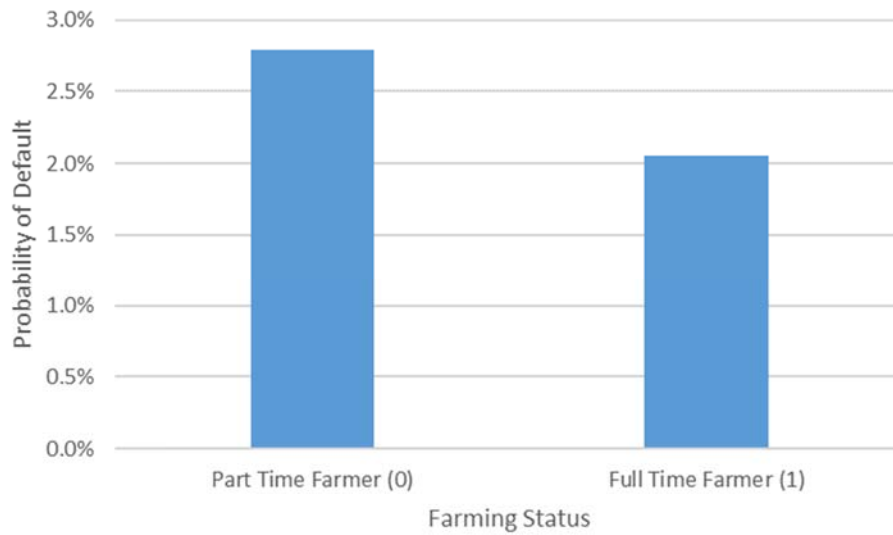
**Figure 5.3: Original Loan Amount of Delinquent Loans**



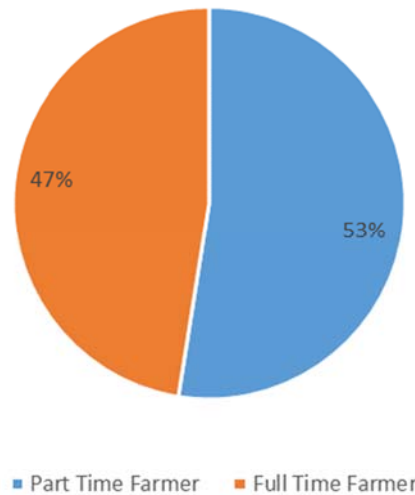
The coefficient for Farming Segment is negative. Since this is a dummy variable where 0 is part time farmer and 1 is full time farmer, the negative coefficient indicates that if you are a full time farmer you are less likely to be delinquent than a part time farmer. Full time farmers are .73% less likely to default than part time farmers. Figure 5.4 shows the change in Probability of Default (chance of delinquencies) as percentage of Full Time Farmer increases while all other variables are held at their mean. This coefficient did not match the hypothesized sign. The farming segment negative coefficient can be rationalized as part time farmers who borrow through Farm Credit Express are probably taking out small loans and are more likely to have no other lending relationship with AgChoice compared to full-time farmers. Of the 2,896 FCE loans, 1,114 loans were made to part time farmers. Of those 1,114 FCE loans to part-time farmers, only 190 borrowers had

additional loans with AgChoice. In the case of cash flow shortage, it is reasonable that part-time farmers would choose to pay other creditors, like their primary mortgage holder, before making payments on a Farm Credit Express financed piece of equipment. With a p-value of 0.1038, this variable is not statistically significant. Figure 5.5 shows the breakdown of farming segment for the 139 delinquent FCE loans.

**Figure 5.4: Impact of Percent Full Time Farmer on Probability of Default**

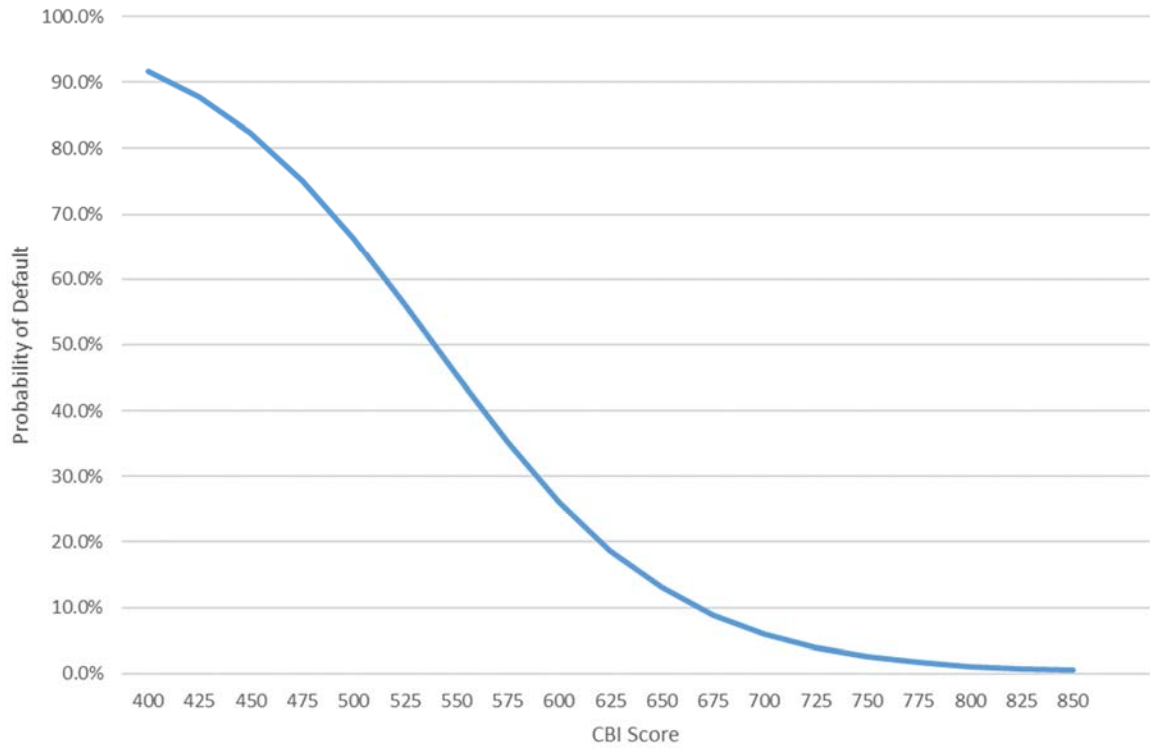


**Figure 5.5: Percent of Delinquencies per Farming Segment**

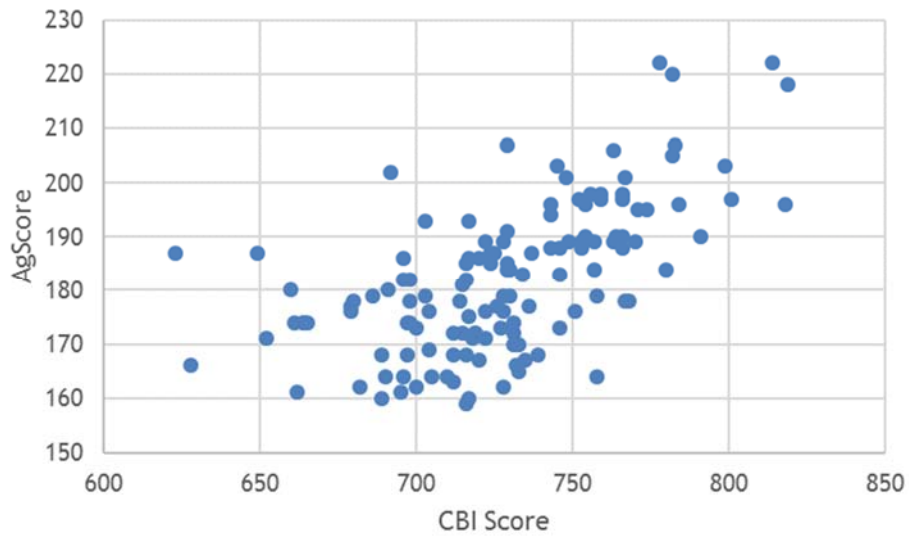


The coefficient for CBI Score is -0.017, which indicates that as CBI Score increases risk for delinquency decreases. CBI score has a very small p-value and is statistically significant at the 1% level. For every one point increase in CBI score borrowers are .04% less likely to default. Figure 5.6 shows the change in Probability of Default (chance of delinquencies) as CBI Score increases while all other variables are held at their mean. Internally, AgChoice has a minimum CBI cutoff of 700. If the CBI score is under 700, an additional 0.25% is added to the interest rate margin. Of the 139 FCE loans that were delinquent, 36 loans, or 25.90% had a CBI score less than 700.

**Figure 5.6: Impact of CBI Score on Probability of Default**



**Figure 5.7: CBI Score and AgScore of FCE Loans with Delinquencies**



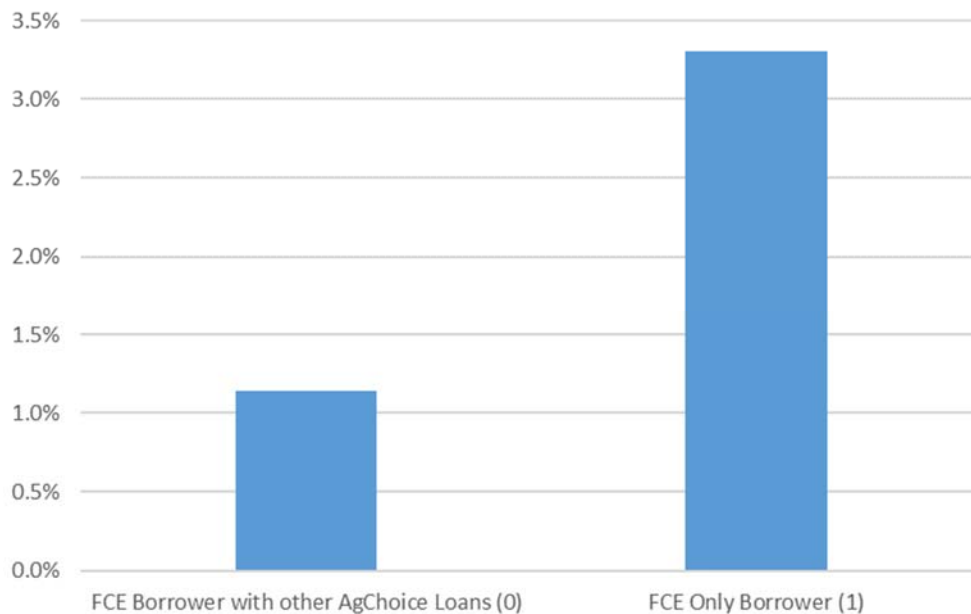
The AgScore variable was not included in the final model. Figure 5.7 above shows the AgScore versus CBI score of the FCE loans that were delinquent at least once during the

past four years. Note, that seven of the 139 delinquent FCE loans had a CBI Score of 0. These seven loans were not included in the scatter plot. The shape of the scatter plot indicates multicollinearity between AgScore and CBI Score.

As the chart indicates, loans that went delinquent had a variety of AgScores. Currently, the AgScore cutoff for FCE approvals is 160. Of the 139 loans, only 1, or 0.72% had a score below 160. Currently, AgChoice’s AgScore cutoff for approval of internal loans that are not processed through the FCE program is 170. Of the 139 loans that were delinquent, 26 loans, or 18.7% had an AgScore less than 170.

The coefficient of the final variable, FCE Only Loans, was positive at 1.08. This variable is statistically significant at the 1% level with a p-value of 0.0012. Figure 5.8 shows the change in Probability of Default (chance of delinquencies) as the Percent FCE Only Loans increases while all other variables are held at their mean.

**Figure 5.8: Impact of Percent FCE Only Loans on Probability of Default**





## **5.2 Summary**

Logistic regression was used to determine which independent variables had a statistical impact on the dependent variable (FCE delinquencies). Four of the five independent variables were statistically significant at the 1% level.

## CHAPTER VI: CONCLUSION AND FUTURE ANALYSIS

### 6.1 Future Analysis

After researching, collecting data and estimating the regression, it is evident that there are other areas that can be addressed in future research. The data for this study were based on loans that went over 30 days delinquent at least once in four years. These data were chosen because they were readily available from AgChoice's current loan system. The current procedure for servicing delinquent loans is to send past due letters at 20 days delinquent and to make at least one phone call to try and collect before 30 days delinquent. Therefore, there may be loans that reach 29 days past due which are a servicing burden to field staff that are not represented in the data for this thesis project. Future research to evaluate FCE loans at varying days past due would be beneficial to further evaluate the servicing burden on field staff.

While several of the variables were statistically significant, there may be other variables that better predict delinquency. Some other variables to consider would be type of equipment purchased (new versus used), primary industry of borrower (dairy, swine, poultry, etc.), borrower's location and frequency of payment. The Farm Credit Express program finances a lot of used equipment because other dealer financing options like John Deere Financial may not. By including a variable for type of equipment purchased, AgChoice could determine if there is more risk in financing used equipment versus new. A variable for borrower's primary industry could help determine if one agricultural industry has more risk than another. A borrower's location could determine if we have more risk for delinquencies in certain areas of our geographic territory. Finally,

frequency of payment could determine if there is more risk for delinquency with annual payments, versus quarterly or monthly payments.

## **6.2 Recommendations**

Based on the results from the estimated regression model, there are several recommendations that AgChoice could consider to manage risk in its Farm Credit Express portfolio: add a minimum CBI cutoff requirement for FCE approvals, price differentially for FCE only borrowers, and institute a minimum FCE loan amount.

Considering that the CBI Score variable is statistically significant at the 1% level, it is a good predictor of delinquencies. AgChoice could implement the same minimum CBI score that it has for internal loan applications, which is a 700 cutoff. Of the 2,896 FCE loans in the data set, 335 loans, or 11.57% had a CBI score below 700. Another option is to continue to approve loans based on AgScore but require additional interest rate margin for loans with a CBI score under 700 to compensate AgChoice for the additional risk in the account. The amount of additional margin could be calculated using probability of default. Another option to compensate for additional risk is to require an additional upfront origination fee for borrowers with a CBI score below 700.

Based on the data, FCE only loans are more likely to default than borrowers who have additional non-FCE loans with AgChoice. To compensate for this risk, AgChoice could price FCE only loans higher than for FCE borrowers who have additional business with AgChoice. It is recognized that FCE only borrowers may be AgChoice prospects and an FCE loan is a good lead-in product for additional financing. Therefore, the recommendation is not to price FCE only loans out of the market but consider adding additional margin to compensate for the risk.

The final recommendation is to consider implementing a minimum loan amount. While the variable for original loan amount did not indicate that smaller loans are more delinquent, when reviewing Figure 5.1, 50% of the loans were under \$25,000. Creating a minimum loan amount of \$25,000 would reduce number of loans in the program and reduce loan volume. Of the 2,896 FCE loans in the data set, 1,455 loans, or 50.24% had an original loan amount under \$25,000. These 1,455 loans original volume totaled \$20,904,111, which is 20.6% of the 2,986 total FCE loans original volume of \$101,338,293. This recommendation would require additional research to determine if much additional business comes from FCE loans under \$25,000.

It is noted that AgChoice partners with Mid-Atlantic Farm Credit on the Farm Credit Express program, so to implement these recommendations would require all associations that participate in the FCE program to agree.

### **6.3 Conclusions**

This thesis research was prompted by the servicing AgChoice's field staff does to manage Farm Credit Express delinquencies. Researching and collecting data for this thesis project has prompted AgChoice management to evaluate options for managing FCE delinquencies. In March 2018, AgChoice implemented a new procedure for managing FCE only delinquencies. This is for borrowers who only have an FCE loan and have no other business with AgChoice. If an FCE only loan goes over 30 days past due, branch staff have the ability to transfer this loan to AgChoice's Special Asset Group ("SAG") for collection and servicing. Historically, the branch would manage delinquencies until the loan was considered seriously delinquent (nearing 90 days past due) and the loan was transferred to SAG for foreclosure. Now, branch staff have the option at 30 days

delinquent to transfer the account to a SAG loan officer to manage the servicing. Based on this procedure change, the overall thesis project is considered a success by allowing field staff more time to service new, productive loans for the association.

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