Probability of default in farm real estate loans

by

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B.S., Kansas State University, 2023

A THESIS

submitted in partial fulfillment of the requirements for the degree

MASTER OF SCIENCE

Department of Agricultural Economics
College of Agriculture

KANSAS STATE UNIVERSITY
Manhattan, Kansas

2026

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Abstract

Accurately estimating the probability of default is essential for agricultural lenders to evaluate borrower risk and make informed lending decisions. This study develops an updated probability of default framework for agricultural real estate loans using data from the Federal Agricultural Mortgage Corporation (Farmer Mac) from 2001 to 2025. Building on the framework established by Featherstone, Roessler, and Barry (2006), the analysis evaluates default risk using both Point in Time and Through the Cycle approaches.

Logistic regression models are estimated using borrower financial characteristics, loan characteristics, farm type, prior delinquency behavior, and macroeconomic conditions. The analyses use 13,967 individual loans matched with national- and state-level economic indicators.

Results indicate that greater repayment capacity is associated with lower default risk, while higher leverage and larger loan amounts are associated with increased probability of default. Delinquency history exhibits a strong retrospective association with default in the Point in Time analysis, while macroeconomic conditions provide statistically significant associations but only modest improvements in Through the Cycle model discrimination. Overall, the findings demonstrate the importance of borrower financial condition and repayment history in agricultural credit risk assessment, while highlighting the complementary role of broader economic conditions in understanding default risk over time.

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Acknowledgements

I would first like to express my sincere gratitude to my major professor, Dr. Megan Hughes, for her guidance, encouragement, and support throughout this research. Her willingness to share her knowledge, provide thoughtful feedback, and invest in my development as a student and a person has been invaluable. I am especially thankful for her patience and encouragement throughout the challenges of completing this thesis.

I am also incredibly grateful to Dr. Jennifer Ifft for the time, expertise, and guidance she contributed to this research. Her thoughtful insights, constructive feedback, and willingness to work through challenges with me have been instrumental in shaping this thesis. I especially appreciate her investment in my development as a student and the opportunity to learn from her throughout this process.

I would also like to thank Dr. Allen Featherstone for serving on my committee and sharing his expertise in agricultural finance and credit risk modeling. His previous research provided an important foundation for this study, and I am grateful for the opportunity to build upon his work and benefit from his guidance. I am equally grateful to Ryan Kuhns for his assistance in facilitating access to the Farmer Mac data used in this study. His willingness to share his knowledge and provide insight into the practical applications of agricultural credit risk modeling helped connect this research to the agricultural lending industry.

I am deeply thankful for my family and friends, whose love, encouragement, and support have carried me throughout my graduate studies. I am especially grateful to my parents for always pushing me to do the best I can and not just settle for good enough. Their support has meant more to me than words can express.

Above all, I give thanks to my savior Jesus Christ, whose grace has been the foundation of my life and whose faithfulness has carried me through every season. We were created to know and glorify God, yet our sin separates us from Him. But God, in His great love, sent His son, Jesus Christ, to live the perfect life we never could and die the death that we deserved. Through His death on the cross and resurrection, Jesus conquered sin and death, offering forgiveness and eternal life to all who place their faith in Him. This salvation is not something we can earn through our own accomplishments or good works, but a gift of grace received through faith. More than any degree, achievement, or opportunity, my greatest hope and joy is found in knowing Jesus Christ and making Him known.

Chapter 1 - Introduction

An essential job of agricultural lenders is to accurately and efficiently assess borrower and loan characteristics to help manage the risk of the loan defaulting. Access to credit allows farms to survive and cope with the variability in farm and off farm income as well as grow by enabling the adoption of technologies and economies of scale (Key, 2022). Agricultural lending is uniquely volatile compared to other lending types because of external factors like weather, disease outbreaks, and commodity prices which can impact farm profitability and repayment capacity. It is crucial for lenders to be able to accurately assess the likelihood that a borrower will default. Doing so allows lenders to price loans appropriately, manage risk, and continue to provide credit to agricultural producers.

Accurate default prediction can be a challenge because risk rating systems must account for both borrower and loan-specific characteristics as well as changing economic conditions. Most risk rating systems use quantitative and qualitative variables of a loan (Featherstone, Roessler, and Barry, 2006). However, a limitation of those risk rating systems is their reliance on historical financial information that was generated under economic conditions that may not hold true in the future (Featherstone, Roessler, and Barry, 2006). The predictive ability of existing models may decline as agricultural markets, farm structures, and macroeconomic conditions evolve, leading to the need for updated approaches.

The objective of this paper is to develop an accurate and updated probability of default model for agricultural real estate loans using data from the Federal Agricultural Mortgage Corporation, commonly known as Farmer Mac. Farmer Mac is a federally chartered secondary market institution that provides liquidity to agricultural lenders through the purchase and guarantee of agricultural loans. Because Farmer Mac operates across all 50 states and works with a diverse set

of agricultural lenders, its loan portfolio provides a unique opportunity to examine agricultural credit risk at a national scale. The data used has loans from all 50 states from 2001 to 2025 and includes both farm- and loan-level information. This is aggregated with macroeconomic variables to help understand how agricultural loan default changes over time. A logit model is used to estimate the probability of default as a function of borrower financial characteristics, loan characteristics, and broader economic conditions.

Work by Featherstone et al. (2006) is foundational in developing a probability of default model and risk rating framework. They used farm loans in the Seventh Farm Credit District from 1995 to 2002 to do so. They found that borrower financial characteristics such as owner equity, working capital, and commitment amount were important predictors of default. Other studies have built on this in other states and countries such as Illinois (Katchova and Barry, 2005) and France (Jouault and Featherstone, 2011), while others have looked more specifically at credit scoring models (Durguner and Katchova, 2007; Jacobson and Roszbach 2003). Findings from these studies corroborate Featherstone et al. (2006), but they are limited by geography or older data. This creates a need for a broader and updated model of agricultural loan default.

Despite the contributions of previous agricultural credit risk studies, several gaps remain in understanding agricultural loan default. Much of the existing literature relies on data from a particular state, region, or lending institution and reflects agricultural and economic conditions from earlier time periods. As a result, less is known about whether the financial characteristics identified as important predictors of default continue to hold across a more recent and geographically diverse portfolio of agricultural loans. In addition, previous models have primarily emphasized borrower financial condition and loan characteristics, giving less attention to how changes in the broader economic environment may contribute to default risk over time.

This creates an opportunity to evaluate agricultural loan default using both Point in Time (PIT) measures of borrower and loan risk and a Through the Cycle (TTC) framework that incorporates changing economic conditions. Examining these components together can provide a more complete understanding of the factors associated with agricultural loan default and whether those relationships have remained consistent over time.

This study has three major contributions to the literature. First, the dataset contains loan observations from all 50 states of the United States. This allows for broader assessment of agricultural credit risk than studies that focus on a single state or region because it can go beyond regional economic and production influences. Second, the dataset is current and continuous, capturing recent changes in farm structure, macroeconomic conditions, and risk exposure. Lastly, this study aggregates loan-level data with broader economic conditions to provide a more complete understanding of how borrower characteristics and external conditions influence risk and loan default outcomes. The results of this study provide lenders, policymakers, and researchers an updated model to predict default and make decisions based on current markets and practices.

The remainder of this paper is organized as follows. The next section provides background on agricultural lending and reviews previous studies on agricultural risk rating and loan default. Chapter 3 describes the dataset, the variables used, and outlines the model and empirical methods for predicting default. Chapter 4 will present the results of our findings and additional analysis. The paper ends with a conclusion and ideas for further research.

Chapter 2 - Background and Related Literature

Agricultural Credit Risk and Credit Modeling

Agricultural lending presents unique challenges for financial institutions because farm businesses operate in an environment characterized by uncertainty, changing commodity prices, seasonal cash flows, and substantial capital requirements. Agricultural producers often take on significant operating expenses before receiving revenue from the sale of their products, creating potential liquidity constraints and increasing their exposure to poor economic conditions. Furthermore, agricultural borrowers in aggregate experience financial difficulties due to exposure to commodity markets, weather conditions, and regional economic factors. Katchova and Barry (2005) emphasized that these characteristics can create correlated credit risks within agricultural loan portfolios, particularly when lending institutions have significant geographic or industry concentrations. Consequently, agricultural lenders must evaluate both the financial condition of individual borrowers and the potential risk associated with their overall loan portfolios.

Credit risk models provide a quantitative framework for evaluating borrower creditworthiness and estimating the likelihood of default. These models allow financial institutions to incorporate borrower characteristics and financial information into lending decisions while supporting portfolio monitoring and risk management. Jacobson and Roszbach (2003) examined the relationship between credit scoring, bank lending policies, and portfolio credit risk using Swedish consumer credit data. The authors developed a bivariate probit model to address sample selection bias associated with estimated default probability using only approved loan applications. Individual default probability estimates were then incorporated into a Value At Risk framework to evaluate how alternative lending decisions affected portfolio size,

expected losses, and overall credit risk. Their findings found that selecting borrowers based on estimated default risk could substantially reduce portfolio credit risk. Although their analysis focused on consumer lending, the study demonstrated the usefulness of statistical credit scoring models for improving lending decisions and managing financial risk.

The probability of default (PD) is a central component of credit risk modeling and represents the estimated likelihood that a borrower will default over a specified period. In addition to estimating individual default probability, lenders may assign borrowers to risk rating categories based on different levels of creditworthiness. These classifications allow lenders to evaluate the distribution of risk within their portfolios and support decisions regarding loan pricing, monitoring, and capital allocation. Katchova and Barry (2005) examined the application of credit risk models to agricultural lending under the New Basel Capital Accords using CreditMetrics and Moody's KMV methodologies. Their analysis incorporated probability of default, loss given default, and expected and unexpected credit losses to estimate lender capital requirements. Results indicated that capital requirements varied substantially depending on portfolio risk characteristics and the level of differentiation among borrowers. Both approaches assigned greater capital requirements to higher risk credit classes, emphasizing the importance of developing risk rating systems that adequately distinguish borrowers with different levels of credit risk.

Development of Agricultural Probability of Default Models

The development of agricultural probability of default models has increasingly emphasized the use of borrower financial characteristics. Featherstone, Roessler, and Barry (2006) provided a foundation of this approach by examining 157,853 loans from the Seventh Farm Credit District portfolio. Using binomial logistic regressions, the authors estimated the

probability of loan default based on financial characteristics measured at loan origination. Their model emphasized three primary measures of borrower financial condition: repayment capacity, owner equity, and working capital. These variables represented the borrower's ability to meet debt obligations, overall financial solvency, and available liquidity. The results demonstrated that financial ratios could provide useful information for estimating agricultural loan default probabilities and established a framework for evaluating credit risk using information available during the loan underwriting process.

An additional contribution of Featherstone, Roessler, and Barry (2006) was the development of a more detailed risk rating classification system based on estimated default probabilities. The authors related predicted default probabilities to Standard and Poor's credit rating categories and Farm Credit System risk rating guidelines, allowing individual loans to be classified according to their estimated level of credit risk. The average estimated probability of default was 1.61%, corresponding to a Standard & Poor's BB rating under the historical mapping used in the study. By comparing predicted and observed default rates across risk classes, the authors examined the ability of their classification system to distinguish among borrowers with different levels of creditworthiness. This approach demonstrated how default probability estimates could be translated into risk rating categories for agricultural loan portfolio management.

Farm Characteristics and Agricultural Creditworthiness

Building on this framework, Brewer et al. (2012) applied the credit risk model developed by Featherstone, Roessler, and Barry (2006) to evaluate the financial health of U.S. production agriculture. Using farm-level data from the USDA Agricultural Resource Management Survey (ARMS) between 1996 and 2010, the authors calculated synthetic probabilities of default and

assigned corresponding Standard & Poor's credit ratings to individual farms. Rather than estimating a new default model, the study applied the previously developed, Featherstone, Roessler, Barry (2006), logistic regression equation using measures of capital debt repayment capacity, owner equity, and working capital. Estimated default probabilities were examined across farm types, geographic regions, and gross sales classes to identify differences in financial risk throughout the agricultural sector. Results indicated that the average predicted probability of default declined from 1.18% in 1996 to 0.92% in 2010, although variation existed across agricultural operations. Among farms with debt, poultry and hog operations exhibited higher average predicted default probabilities than most crop operations. Larger farms generally exhibited greater estimated default risk than smaller farms. Regional differences were also observed, with the Delta region (Arkansas, Louisiana, and Mississippi) exhibiting the highest average predicted probability of default and the Corn Belt (Illinois, Indiana, Iowa, Missouri, and Ohio) exhibiting the lowest. These findings demonstrated the applicability of agricultural credit scoring models beyond individual lending portfolios and highlighted differences in estimated credit risk across agricultural enterprises.

Other studies have examined whether the relationships between financial characteristics and creditworthiness differ across agricultural production types. Parcell, Ifft, and Roach (2025) used Kansas Farm Management Association records to estimate farm-level default probabilities and found higher estimated risk among farms with lower net farm income and higher operating expense ratios. Durguner and Katchova (2007) evaluated farm type-specific credit scoring models using Illinois Farm Business Farm Management data from 1995 through 2004. The authors estimated logistic regression models for hog, dairy, beef, and grain operations, classifying borrowers according to creditworthiness using a debt coverage ratio threshold.

Explanatory variables included measures of liquidity, solvency, profitability, financial efficiency, and land tenure. Their findings identified working capital relative to gross farm returns, debt-to-asset ratio, and return on farm assets as important determinants of creditworthiness. The relationships between certain financial characteristics and creditworthiness also differed across farm types, particularly between hog and grain operations. These results suggested that agricultural credit scoring models may benefit from accounting for differences in production characteristics rather than assuming financial ratios have uniform effects across all agricultural enterprises.

Jouault and Featherstone (2011) further examined agricultural default prediction using 756 agricultural loans from a French bank. Applying binomial logistic regression, the authors evaluated the relationship between financial characteristics observed at loan origination and subsequent default outcomes. Their results indicated that leverage, profitability, and liquidity were significant predictors of agricultural loan default. Higher leverage, lower profitability, and lower liquidity as well as longer loan terms were associated with greater default probabilities. The authors also examined differences across loan activities and collateral types, suggesting that more specialized model specifications could improve predictive performance. Their findings reinforced the importance of borrower financial characteristics in agricultural default prediction while demonstrating that the relationships between these characteristics and default may vary across lending portfolios.

More recently, Ferch (2023) estimated agricultural loan default probabilities using ten years of historical AgriFinancial loan data. The study employed a binomial logistic regression model with explanatory variables of financial and credit characteristics measured at origination. Credit score, Debt-to-Asset ratio, three year average total debt coverage, and original principal

were identified as statistically significant predictors of default. Higher Debt-to-Asset ratios and larger original principal amounts were associated with greater default risk, while higher credit scores and stronger debt coverage were associated with lower default probabilities. These findings provided additional evidence supporting the use of financial characteristics and loan size in agricultural default modeling.

Risk Rating Migration and Macroeconomic Conditions

Although borrower financial characteristics provide useful information for estimating default risk, agricultural financial conditions may change substantially throughout the life of a loan. Changes in repayment capacity, liquidity, asset values, and leverage may alter borrower creditworthiness and result in movement between risk rating categories. Featherstone, Wilson, and Zollinger (2017) examined risk rating migration using 17,943 observations from a Farm Credit System association between 2006 and 2012. The authors used ordinary least squares regression to evaluate how current risk ratings and financial ratios predicted borrower risk ratings one, three, and five years into the future. Their findings indicated that current financial information was useful in forecasting future risk ratings, particularly over shorter periods of time. Debt-to-asset ratios were important predictors of future risk ratings, while the predictive usefulness of some financial measures declined over longer horizons. These findings emphasized the importance of regularly updating borrower financial information and demonstrated that credit risk assessments may change as the financial condition of agricultural operations evolve.

In addition to changes in borrower financial characteristics, broader agricultural and macroeconomic conditions may influence credit risk over time. Johnson, Boehlje, and Gunderson (2017) examined the relationship between farm-level, agricultural sector, and macroeconomic variables and changes in borrower probability of default ratings. Using data

from 153 grain farms in the Farm Credit Mid America portfolio, the authors estimated ordered logit models to evaluate factors associated with risk rating migration. Their findings indicated that farm-level and sector-level financial measures, including equity-to-asset ratios, working capital relative to gross farm income, and gross corn income per acre, were more reliable predictors of changes in borrower risk ratings than broader macroeconomic variables. Although macroeconomic measures did not consistently improve predictive performance, the study demonstrated the importance of evaluating economic conditions alongside borrower financial characteristics when examining changes in agricultural credit risk.

Collectively, previous research demonstrates that borrower financial characteristics, including repayment capacity, leverage, liquidity, and loan size, are important determinants of agricultural credit risk. Studies have also established frameworks for estimating default probabilities, assigning borrowers to risk rating categories, and examining differences in creditworthiness across agricultural enterprises. More recent research has extended these approaches to evaluate changes in borrower risk ratings and the influence of broader economic conditions. However, these studies differ in their measures of credit risk, modeling approaches, and the populations examined. Distinctions between observed loan defaults, financial ratio based creditworthiness classifications, and risk rating migration are important when comparing findings across studies. Together this literature provides the foundation for evaluating agricultural loan default using borrower financial characteristics, loan-level information, and changing economic conditions.

Chapter 3 - Data and Methodology

This chapter describes the data and empirical methods used to examine agricultural loan default. The analysis combines agricultural real estate loan data from Farmer Mac with measures of broader economic conditions to evaluate default risk from both Point in Time (PIT) and Through the Cycle (TTC) perspectives. The chapter first describes the Farmer Mac dataset, borrower and loan characteristics, delinquency measures, macroeconomic variables, and descriptive statistics. The PIT analysis then examines default at the individual loan-level using borrower financial conditions, loan characteristics, farm type, and prior delinquency behavior. The TTC analysis uses an annual loan-year panel to examine how default risk is associated with changing economic conditions over time. Macroeconomic conditions are measured using annual CPI inflation, annual real GDP growth, and state-level net cash farm income. Additional specifications incorporate one-year lagged macroeconomic variables to examine whether economic conditions in the preceding year are associated with subsequent loan default. Finally, a credit risk classification system is developed using predicted probabilities of default from the baseline PIT model following the methodology of Featherstone, Roessler, and Barry (2006). This assigns loans to risk rating classes to evaluate differences in financial characteristics and observed default experience across risk categories. Together, these approaches allow the analysis to distinguish the relationships between loan-specific characteristics and default from those associated with changes in the broader agricultural economic environment.

The study uses publicly available loan panel data from Farmer Mac, covering the period from 2001 to 2025. It contains 18,472 unique agricultural real estate loans across all fifty states with monthly observations. The dataset contains detailed loan and farm characteristics. Key loan-level variables are Loan Amount, Unpaid Principal Balance, and Combined Loan to Value Ratio.

Farm-level variables are Total Debt Coverage Ratio, Debt-to-Asset Ratio, and Current Ratio (Table 3.2). Monthly delinquency codes ranging from 1 to 8 are also included. Higher values indicate greater levels of delinquency severity as listed in Table 3.1. In addition, there are commodity classifications and geographic identifiers for each loan. Missing values were addressed during the data import to ensure consistency across variables.

Table 3.1 Delinquency Indicators

Indicator	Corresponding Delinquency
1	Current
2	30 – 59 days past due
3	60 – 89 days past due
4	90 – 179 days past due
5	180+ days past due
6	Foreclosure
7	Non-performing Bankruptcy
8	Performing Bankruptcy

Several processes were completed prior to estimation. First, all data variables were converted into a standardized month/day/year format to ensure consistency across observations. The primary default indicator defines default as a loan reaching delinquency code 4 or greater, corresponding to 90 or more days past due. For the PIT models, loans that reached this threshold at any point during the sample period were assigned a value of one, while loans that did not were assigned a value of zero. For the TTC analysis, the default indicator is defined separately for each loan-year observation, taking a value of one when the loan's delinquency code reached 4 or greater during the calendar year and zero otherwise. Delinquency code 4 was selected as the primary threshold because it represents a more severe stage of repayment distress and provides a conservative measure of agricultural loan default. An alternative indicator defining default at delinquency code 3 or greater was also constructed and is used only as a robustness check to evaluate whether the primary results are sensitive to a less restrictive default definition.

Additional dummy variables were created for year effects, commodity groups (both major and minor), and state identifiers. Major commodity group indicators classified loans into categories including crops, livestock, permanent plantings, and not specified/other. Then minor commodity group indicators broke that down into more specific classifications within them. State dummy variables were also generated for all 50 states included in the sample.

Table 3.2 Variable Definitions

Variable Name	Definition
Total Debt Coverage Ratio	Total borrower cash flow available to service debt divided by the total borrower annual principal and interest payments known at the time of origination or purchase (proforma where available)
Original Loan to Value Ratio	Loan amount divided by collateral value at the time of purchase
Debt-to-Asset Ratio	Total borrower liabilities divided by total borrower assets known at the time of origination or purchase (proforma where available)
Loan Amount	Loan balance at the time of commitment or purchase
Log Loan Amount	Natural logarithm of Loan Amount
Major Commodity Group	Primary commodity type of underlying collateral (crops, livestock, permanent planting)
Livestock	Indicator equal to 1 if the loan is classified in the livestock major commodity group and 0 otherwise
Permanent Plantings	Indicator equal to 1 if the loan is classified in the permanent plantings major commodity group and 0 otherwise
Crops	Indicator equal to 1 if the loan is classified in the crops major commodity group and 0 otherwise
Not Specified/Other	Indicator for loans not classified as livestock, permanent plantings, or crops
Current Delinquency Code	Periodic monthly delinquency indicator
Ever Delinquent: 2+	Indicator equal to 1 if a loan ever reaches delinquency code 2 or greater during its observed history and 0 otherwise
Ever Delinquent: 3+	Indicator equal to 1 if a loan ever reaches delinquency code 3 or greater during its observed history and 0 otherwise
Consumer Price Index (CPI)	Annual average of the national Consumer Price Index obtained from FRED, measuring the general price level
Annual CPI Inflation (%)	Annual percentage change in the average CPI relative to the preceding calendar year
Lagged CPI Inflation (%)	Annual CPI inflation observed in the preceding calendar year (t-1)
Real GDP	Annual average of US gross domestic product obtained from FRED, adjusted for inflation, measuring national economic output
Annual Real GDP Growth (%)	Annual percentage change in real GDP relative to the preceding calendar year
Lagged Real GDP Growth (%)	Annual real GDP growth observed in the preceding calendar year (t-1)

State Net Cash Farm Income ($ Billion) *Or Net Cash Income*	State-level agricultural cash income after cash expenses, obtained from USDA ERS and expressed in billions of dollars
Lagged State Net Cash Farm Income ($ Billion)	State net cash farm income observed in the preceding calendar year (t-1)
Annual Default at Code 4+	Indicator equal to 1 if a loan reaches delinquency code 4 or greater during any month of the calendar year, and 0 otherwise
Annual Default at Code 3+	Indicator equal to 1 if a loan reaches delinquency code 3 or greater during any month of the calendar year, and 0 otherwise

To incorporate broader economic conditions into the TTC analysis, the Farmer Mac loan data was supplemented with macroeconomic data from the U.S. Department of Agriculture Economic Research Service (ERS) and the Federal Reserve Economic Data (FRED) database. The original monthly loan observations were aggregated into annual loan-year observations, allowing each loan to contribute one observation for each calendar year in which it appeared in the portfolio. National economic measures were matched to the annual loan observations by year, while state-level agricultural measures were matched using the state in which the loan was located and the corresponding calendar year of the monthly portfolio observation. This approach allows the TTC analysis to retain changes in borrower and loan characteristics over time while incorporating the broader economic environment. The final TTC estimation sample includes 83,052 loan-year observations with complete macroeconomic data through 2024. The lagged specifications use 82,652 loan-year observations for which the preceding year's macroeconomic measures are available.

The macroeconomic variables were selected to capture both broader national economic conditions and state-level agricultural conditions. The Consumer Price Index (CPI) obtained from FRED, measures changes in the general price-level over time, while Real Gross Domestic Product (Real GDP) provides a measure of national economic activity adjusted for inflation. Annual CPI Inflation and Real GDP Growth were calculated as the percentage change in the corresponding annual average from the preceding year. These measures capture changes in

economic conditions rather than the levels of underlying indicators. State-level agricultural conditions are measured using Net Cash Farm Income (NCFI) from ERS, which captures cash income generated by the farm sector after cash expenses. Unlike the national economic indicators, State NCFI varies across both states and years. Together, these variables allow the analysis to examine how national economic changes and state-level agricultural financial conditions are associated with annual agricultural loan default. Additional models incorporate one-year lagged values of these macroeconomic indicators to evaluate whether economic conditions in the preceding calendar year are associated with subsequent loan repayment difficulties.

Annual CPI Inflation

$$CPI\ Inflation_t = 100\left(\frac{CPI_t}{CPI_{t-1}} - 1\right)$$

Annual Real GDP Growth

$$GDP\ Growth_t = 100\left(\frac{GDP_t}{GDP_{t-1}} - 1\right)$$

The length of observed loan histories varies considerably across the sample. Loans are observed for an average of 65 months or 5.4 years, with a median observation period of 58 months. The shortest loan is observed for one month, while the longest is observed for 242 months, or just over 20 years.

Table 3.3 Loan Summary Statistics

N	Shortest	Q1	Median	Mean	Q3	Longest	SD
13967	1	38	58	65.03	87	242	39.26

Default events represent a relatively small share of the agricultural real estate loans included in the PIT sample. Of the 13,967 loans, 356 loans or 2.55 percent, reached delinquency code 4 or higher during the sample period. Under the less restrictive definition of default, code 3 or higher, 574 loans reached default, or 4.11 percent. These results illustrate the relatively low frequency of severe default events in the Farmer Mac portfolio while also indicating that a larger

group of borrowers experienced repayment difficulties before reaching the more severe default thresholds.

Table 3.4 Alternative Default Definition Percentages

Outcome	Defaults	Total	Percent
Default at 3+ (60-89 days)	574	13967	4.11
Default at 4+ (90-179 days)	356	13967	2.55

The financial characteristics of loans in the sample also provide context for the regression analysis. The mean Total Debt Coverage Ratio was 1.675, while the mean Original Loan to Value Ratio was 0.452, and the mean Debt-to-Asset Ratio was 0.265. Crop loans represented the largest farm type category, accounting for approximately 71.1 percent of the sample, compared to 14.3 percent for livestock and 14.4 percent for permanent plantings.

Table 3.5 PIT Variable Summary Statistics

Variable	Count	Mean	Std. Dev	Min	Max
Default at 4+ (90-179 days)	356	0.025	0.158	0.000	1.000
TDC Ratio	13967	1.675	1.349	0.000	8.253
Original LTV Ratio	13967	0.452	0.161	0.005	1.812
Debt-to-Asset Ratio	13967	0.265	0.156	0.000	0.560
Log Loan Amount	13967	13.143	0.972	9.350	16.811
Livestock	1996	0.143	0.350	0.000	1.000
Permanent Plantings	2012	0.144	0.351	0.000	1.000
Crops	9932	0.711	0.453	0.000	1.000
Prior Early Delinquency (3+)	574	0.041	0.194	0.000	1.000
Note: For binary variables, Count is the number of loans with a value of 1. For continuous variables, count is the number of non-missing observations.					

The macroeconomic variables also exhibit variation across the annual TTC estimation sample. Annual CPI Inflation averaged 2.85 percent, with a standard deviation of 1.95 percentage points, and ranged from -0.32 percent to 7.99 percent. Annual Real GDP Growth averaged 2.36 percent, with a standard deviation of 1.92 percentage points, and ranged from -2.58 percent to 6.15 percent. State Net Cash Farm Income, measured in billions of dollars, averaged $7.74 billion, with a standard deviation of $6.49 billion. State NCFI ranged from approximately -$0.023 billion to $30.0 billion, reflecting substantial variation in agricultural economic conditions across states and years. Together, these variables capture changes in

national economic activity and differences in state-level agricultural financial conditions throughout the sample period.

Table 3.6 TTC Variable Summary Statistics

Variable	Count	Mean	Std. Dev	Min	Max
Annual CPI Inflation (%)	83052	2.85	1.95	-0.320	7.99
Annual Real GDP Growth (%)	83052	2.36	1.92	-2.58	6.15
State NCFI ($ Billion)	83052	7.74	6.49	-0.0232	30.0

Defaulting and non-defaulting loan-year observations exhibit several differences in borrower financial and loan characteristics. Defaulting observations have a lower average Total Debt Coverage Ratio of 1.44 compared with 1.69 for non-defaulting observations, indicating weaker repayment capacity among loan-years that ultimately reach the default threshold. Defaulting observations also have a higher average Debt-to-Asset Ratio of 0.330 compared with 0.269 for non-defaulting loans and a higher average Log Loan Amount of 13.5 compared with 13.1. In contrast, Original Loan to Value Ratios are similar between the two groups averaging 0.459 for defaulting observations and 0.450 for non-defaulting observations. These descriptive patterns are consistent with the baseline model results, in which repayment capacity, leverage, and loan size may be more strongly associated with annual default outcomes than the original collateral position.

Macroeconomic conditions also differ between defaulting and non-defaulting loan observations, although the differences in the group means are relatively small. Annual CPI Inflation averaged 2.73 percent for defaulting observations compared with 2.85 percent for non-defaulting observations, while Annual Real GDP Growth averaged 2.18 percent and 2.36 percent, respectively. State NCFI was also lower among defaulting observations, averaging $7.09 billion compared with $7.75 billion for non-defaulting observations. These descriptive comparisons indicate that defaulting loan-years were associated, on average, with slightly lower inflation, economic growth, and state agricultural cash income. However, these differences do

not account for other borrower and loan characteristics, and they should not be interpreted as independent or causal effects. The multivariate TTC models are used to evaluate these relationships while controlling for the other included explanatory variables.

Table 3.7 Default vs Non-Default Definition Summary Statistics

Variable	Mean Default	Mean Non-Default	SD Default	SD Non-Default
CPI Inflation (%)	2.73	2.85	1.80	1.95
Debt-to-Asset Ratio	0.330	0.269	0.146	0.151
GDP Growth (%)	2.18	2.36	2.00	1.92
Log Loan Amount	13.5	13.1	1.01	0.928
State NCFI ($B)	7.09	7.75	6.77	6.48
Original LTV	0.459	0.450	0.151	0.157
TDC Ratio	1.44	1.69	0.976	1.30

These descriptive patterns provide preliminary evidence of relationships between borrower financial condition, macroeconomic conditions, and agricultural loan default. However, many borrower and loan characteristics are related to one another, and default risk may reflect multiple financial and economic factors simultaneously. The logistic regression models presented in the following sections therefore evaluate these relationships while controlling for multiple characteristics.

Point in Time

The PIT analysis evaluates agricultural loan default risk using borrower financial and loan characteristics observed within the available loan history. The purpose of the PIT framework is to identify characteristics associated with whether a loan experiences default during the sample period. This approach focuses primarily on borrower and loan-specific measures of credit risk, including repayment capacity, leverage, collateral position, and loan size. By estimating default probability using these characteristics, the PIT models provide a measure of how differences in the financial condition and structure of individual loans are associated with default outcomes.

The PIT analysis also provides the foundation for evaluating whether additional information, such as farm type and prior delinquency behavior, improves the prediction of default.

Because the original dataset consisted of monthly panel observations, the data was collapsed into a single observation per loan. This transformation allowed the analysis to focus on overall loan default outcomes rather than monthly fluctuations. Different aggregation rules were applied depending on the variable type. Continuous financial variables, including UPB, CLTV, LTV ratio, and DA ratio, were averaged across the life of each loan. Categorical variables and fixed loan characteristics, like commodity group, state, and loan type, were assigned using the first observed value. Variables associated with rare events, including charge offs and recoveries were captured using the first non-zero observation. Binary indicators and delinquency flags were aggregated using the maximum observed value to identify whether the event occurred at any point during the loan's history. Binary indicator variables were also constructed for loans that ever entered a lower delinquency category prior to default.

Additional cleaning procedures were implemented after collapsing the dataset to reduce the influence of outliers. The extreme observations were addressed by capping several financial ratios at economically reasonable thresholds. TDC ratio and DA ratio were winsorized at 99th percentile. Current ratio was capped at 10 and CLTV was capped at 2. Observations with negative TDC or DA ratios were removed from the sample, as these values were considered economically implausible or indicative of reporting errors. To reduce skewness and improve interpretability, the Loan Amount was transformed using the natural logarithm. This also reduced the influence of extremely large loans in the estimation process. After the cleaning procedures, 13,967 loans remained in the final PIT sample.

This study uses a logistic regression model to estimate the probability of loan default. Because the dependent variable is binary, the logit framework is appropriate for modeling the likelihood that a loan enters delinquency beyond the specified threshold. This is also standard for probability of default models. Model development follows a sequential approach to evaluate the contribution of different categories of explanatory variables. The analysis begins with a baseline specification based on the agricultural credit risk framework developed by Featherstone et al. (2006). This model primarily focuses on farm financial characteristics that reflect repayment capacity, leverage and liquidity. Table 3.8 compares the variables Featherstone et al. (2006) uses versus the corresponding variables of this study. After establishing the baseline model, additional specifications were estimated to examine whether farm type and prior delinquency behavior provide additional information about agricultural loan default risk.

Table 3.8 FRB Variable Comparison

FRB Variable	Corresponding Variable	Why?
Repayment Capacity	Total Debt Coverage Ratio	Both measure debt servicing ability
Owner Equity (inverse LTV)	Original Loan to Value Ratio	Inverse Relationship
Working Capital	Debt-to-Asset Ratio	Captures borrower leverage and financial strength
Commitment Amount	Log Loan Amount	Same underlying loan size variable

The baseline specification uses the Farmer Mac variables that most closely correspond to the financial measures included in Featherstone et al. (2006). Total Debt Coverage Ratio is used to measure repayment capacity, Original Loan to Value Ratio captures the relationship between the loan balance and collateral value, Debt-to-Asset Ratio measures borrower leverage, and the natural logarithm of Loan Amount captures loan size. The subscript i identifies the specific loan and $k \in \{3,4\}$ identifies the default threshold. This provides an updated application of the Featherstone et al. (2006) framework using a more recent and geographically broader portfolio of

agricultural real estate loans while also establishing a consistent baseline against which the subsequent model extensions can be compared.

Baseline FRB specification

$$Logit[P(Default_{ki} = 1)] = \beta_0 + \beta_1 TDC_i + \beta_2 LTV_i + \beta_3 DA_i + \beta_4 ln(LoanAmount_i) + \varepsilon_i$$

The second specification extends the baseline model by incorporating farm type indicators to determine whether default risk differs across agricultural sectors after controlling for borrower financial and loan characteristics. Indicator variables are included for livestock, permanent plantings, and Not Specified, with Crops serving as the omitted reference category. Crops were selected as the reference category because they represent the largest share of the sample. The Not Specified category contains relatively few observations, so estimates for this group should be interpreted cautiously. Like the baseline model, the subscript i identifies the specific loan and k∈{3,4} identifies the default threshold. This specification allows the estimated relationships for the other farm types to be interpreted relative to crop loans, providing a comparison of default risk across agricultural production categories.

Farm-Type Extension

$$Logit[P(Default_{ki} = 1)] = \beta_0 + \beta_1 TDC_i + \beta_2 LTV_i + \beta_3 DA_i + \beta_4 ln(LoanAmount_i) + \beta_5 Livestock_i + \beta_6 PermanentPlantings_i + \beta_7 NotSpecified_i + \varepsilon_i$$

The third specification examines the relationship between delinquency history and severe default. An indicator identifying whether a loan reached delinquency code 3 or greater at any point during its observed history is added to the baseline model. This specification evaluates the association between repayment distress and the primary default threshold of delinquency code 4 or greater. The delinquency indicator is constructed using the observed repayment history of each loan. Because the PIT dataset is collapsed to one observation per loan, the indicator identifies whether a loan experiences the specified level of delinquency at any point during its observed history. Consequently, the indicator may contain information from the same period

used to determine the loan's eventual default outcome. Again the subscript i identifies the specific loan and k∈{3,4} identifies the default threshold. The delinquency extension is therefore interpreted as an assessment of the association between repayment distress and severe default rather than a fully prospective prediction model using only information available before default.

Delinquency Extension

$$Logit[P(Default_{ki} = 1)] = \beta_0 + \beta_1 TDC_i + \beta_2 LTV_i + \beta_3 DA_i + \beta_4 ln(LoanAmount_i) + \beta_5 PriorDelinquency_i + \varepsilon_i$$

To improve interpretability, average marginal effects (AMEs) were computed for the logistic regression models. AMEs convert coefficient estimates into probability changes, allowing economic significance for each variable to be interpreted more directly.

Comparing model performance across these specifications provides insight into the relative importance of farm financial conditions, loan characteristics, and delinquency history on agricultural loan default. Model performance was evaluated using multiple measures of fit and predictive ability. McFadden's pseudo R^2 was used to assess improvement in model fit relative to an intercept only model, with larger values indicating greater explanatory power. Because default represents a relatively small proportion of loans in the sample, model performance was also evaluated using classification accuracy, sensitivity, and specificity. Sensitivity measures the proportion of actual defaults correctly identified by the model, while specificity measures the proportion of non-defaulting loans correctly identified. Considering these measures together provides a more complete assessment of model performance than overall classification accuracy alone.

Because logistic regression produces a predicted probability of default rather than a direct default classification, a probability threshold must be selected to classify loans as predicted

defaults or non-defaults. Loans with predicted probabilities equal to or greater than the selected threshold are classified as predicted defaults, while loans below the threshold are classified as predicted non-defaults. Model performance was evaluated at both 2 percent and 3 percent probability thresholds. The 2 percent threshold was included to provide a direct comparison with the classification approach used by Featherstone et al. (2006), while the 3 percent threshold was examined because it more closely corresponds to the observed 2.55 percent default. Comparing the two thresholds illustrates the tradeoff between sensitivity and specificity as the probability required to classify a loan as a predicted default increases. Lower thresholds generally identify a greater proportion of actual defaults but may also classify more performing loans as defaults, while higher thresholds reduce false positive classifications but may fail to identify a greater proportion of actual defaults. Evaluating multiple thresholds therefore provides a more complete assessment of the practical predictive performance of each model.

Through the Cycle

The TTC analysis extends the PIT framework by incorporating changes in economic conditions over the life of a loan. Agricultural borrowers operate in an economic environment that can change considerably over time, and fluctuations in farm income, agricultural production, input and output prices, and broader price levels may affect a borrower's ability to meet debt obligations. As a result, default risk may reflect not only differences in borrower financial condition and loan characteristics but also the economic conditions borrowers experience throughout the observed loan period. The TTC framework is used to examine whether these changing external conditions provide additional information about agricultural loan default beyond the borrower and loan-specific characteristics included in the baseline models.

The primary distinction between the PIT and TTC analyses is the treatment of the time dimension within the Farmer Mac data. For the PIT analysis, the monthly observations are collapsed to a single observation for each loan, allowing the models to examine whether borrower and loan characteristics are associated with whether the loan experiences default during its observed history. In contrast, the TTC analysis aggregates the original monthly observations into an annual panel containing one observation per loan per calendar year. This structure preserves variation in loan characteristics and economic conditions across years while avoiding the use of multiple monthly observations for the same loan within a given year. The two approaches therefore provide complementary perspectives: the PIT analysis focuses on differences in risk across individual loans, while the TTC analysis examines how annual loan default outcomes are associated with changing economic conditions over time.

To incorporate changing economic conditions into the loan-level analysis, the original monthly Farmer Mac observations were aggregated by loan and calendar year. Each loan was assigned one observation for every year in which it appeared in the dataset. The annual default indicator was constructed using the maximum delinquency status observed during the year, with a value of one assigned when the loan reached delinquency code 4 or greater during at least one month. Annual observations were then matched with macroeconomic information according to the corresponding calendar year and geographic location. National CPI Inflation and Real GDP Growth were matched by year, while State NCFI was matched by both state and year. This process allows the TTC analysis to examine annual default outcomes alongside changing national and state-level economic conditions.

The TTC analysis begins with a baseline specification containing the same borrower financial and loan characteristics used in the PIT baseline model. Total Debt Coverage Ratio,

Original Loan to Value Ratio, Debt-to-Asset Ratio, and Log Loan Amount are included to maintain consistency between the two approaches. Unlike the PIT specification, however, the TTC model is estimated using the panel data rather than a single collapsed observation for each loan. This provides a baseline for evaluating the relationship between borrower and loan characteristics and default within the TTC framework before measures of the broader economic environment are introduced. Maintaining a consistent set of baseline explanatory variables also allows subsequent changes in model fit and predictive performance to be evaluated as macroeconomic information is added. The subscript i identifies the specific loan and t identifies the calendar year.

Baseline FRB specification

$$Logit[P(Default_{it} = 1)] = \beta_0 + \beta_1 TDC_{it} + \beta_2 LTV_{it} + \beta_3 DA_{it} + \beta_4 ln(LoanAmount_{it}) + \varepsilon_{it}$$

The baseline TTC model is extended by incorporating measures of the broader economic environment to determine whether changing economic conditions provide additional information about agricultural loan default. While borrower financial ratios and loan characteristics capture differences in the financial condition of individual borrowers, agricultural repayment capacity may also be affected by economic conditions outside the borrower's direct control. Changes in farm sector income, agricultural economic activity, and the general price environment may alter revenues, production costs, asset values, and ultimately a borrower's ability to service debt. Incorporating macroeconomic variables therefore allows the TTC analysis to evaluate whether variation in default risk over time is associated with changes in the economic environment after controlling for borrower and loan characteristics.

Macroeconomic measures are first introduced individually into the baseline TTC specification. Estimating the variables separately allows the relationship between each economic measure and default to be examined while maintaining the same set of borrower and loan

controls across specifications. This approach also limits the influence of correlation among related macroeconomic measures when evaluating their relationship with default. The macroeconomic variables are subsequently considered together in a combined specification to evaluate their joint contribution to the TTC model. The variable Macro represents one of three macroeconomic measures (annual CPI Inflation, annual Real GDP Growth, or State Net Cash Farm Income) introduced individually into the baseline TTC specification. The subscript i also identifies the specific loan and t identifies the calendar year.

Baseline + specification

$$Logit[P(Default_{it} = 1)] = \beta_0 + \beta_1 TDC_{it} + \beta_2 LTV_{it} + \beta_3 DA_{it} + \beta_4 ln(LoanAmount_{it}) + \beta_5 Macro_{st} + \varepsilon_{it}$$

The macroeconomic extension includes annual CPI Inflation, annual Real GDP Growth, and State Net Cash Farm Income. CPI Inflation measures the annual percentage change in the national price level, while Real GDP Growth measures the annual percentage change in inflation adjusted economic output. State NCFI captures variation in agricultural financial conditions across states and years and is expressed in billions of dollars. Each macroeconomic measure is first introduced separately into the baseline TTC specification, resulting in individual CPI Inflation, GDP Growth, and State NCFI models. The subscript i also identifies the specific loan and t identifies the calendar year. These specifications evaluate whether each measure of the economic environment is associated with annual loan default after controlling for borrower financial and loan characteristics.

Combined Macroeconomic Specification

$$Logit[P(Default_{it} = 1)] = \beta_0 + \beta_1 TDC_{it} + \beta_2 LTV_{it} + \beta_3 DA_{it} + \beta_4 ln(LoanAmount_{it}) + \beta_5 CPIInflation_t + \beta_6 RealGDPGrowth_t + \beta_7 StateNCFI_{st} + \varepsilon_{it}$$

A combined TTC specification is then estimated by including annual CPI Inflation, annual Real GDP Growth, and State NCFI simultaneously with the baseline borrower and loan

characteristics. The combined model evaluates the relationship between each macroeconomic measure and default while controlling for both the borrower specific characteristics and the other measures of the economic environment. Comparing the combined specification with the individual macroeconomic models also provides insight into whether the estimated relationships change when national and state-level economic conditions are considered jointly.

Lagged Macroeconomic Specification

$$Logit[P(Default_{it} = 1)] = \beta_0 + \beta_1 TDC_{it} + \beta_2 LTV_{it} + \beta_3 DA_{it} + \beta_4 ln(LoanAmount_{it}) + \beta_5 CPIInflation_{t-1} + \beta_6 RealGDPGrowth_{t-1} + \beta_7 StateNCFI_{s,t-1} + \varepsilon_{it}$$

Additional TTC specifications incorporate one-year lagged macroeconomic variables to examine whether economic conditions in the preceding calendar year are associated with subsequent agricultural loan default. Annual CPI Inflation, annual Real GDP Growth, and State NCFI are lagged by one year, allowing the economic conditions observed in year t-1 to be associated with the default outcome observed in year t. The lagged variables are introduced individually into the baseline specification and jointly in a combined lagged model. These specifications retain the borrower and loan characteristics while replacing the current-year macroeconomic measures with their preceding-year values. The lagged models provide an additional perspective on the timing of the relationships between economic conditions and agricultural loan repayment difficulties.

The TTC models are estimated using annual loan-year observations with complete borrower, loan, and macroeconomic information. Although the original Farmer Mac dataset contains observations through 2025, complete macroeconomic information was only available through 2024 at the time of pulling the data. The final estimation sample contains 83,052 loan-year observations, including 782 defaulting loan-years, corresponding to an annual default rate of approximately 0.94 percent. All five contemporaneous TTC specifications are estimated using

this common sample. The lagged specifications contain 82,652 loan-year observations for which the preceding year's macroeconomic measures are available. Because the lagged and contemporaneous samples differ, comparisons between these specifications should account for the difference in observations.

An important consideration is that individual loans may contribute observations in multiple calendar years. Consequently, the annual loan-year observations do not represent an equivalent number of independent loans. Additionally, national macroeconomic variables take the same value for all loans observed in a given year, while state-level measures are shared by loans within the same state and year. These features may introduce correlation among observations. The logistic regression models are estimated using conventional model based standard errors, and standard errors for average marginal effects are calculated using the delta method. Because the standard errors do not explicitly account for dependence among repeated loan observations or common economic conditions statistical significance may be overstated. The estimated relationships are therefore interpreted as associations rather than evidence of causal effects.

Model performance is evaluated using measures of both model fit and predictive performance. McFadden's pseudo R^2, the likelihood ratio chi squared statistic, and the Akaike Information Criterion (AIC) are used to compare model fit across the baseline, individual macroeconomic, and combined TTC specifications. Predictive performance is evaluated using the area under the receiver operating characteristic curve (AUC), which measures the ability of each model to distinguish between defaulting and non-defaulting observations.

Classification performance is also examined using a common predicted probabilities of default and a common cutoff threshold of 0.90 percent across the contemporaneous TTC models.

This threshold is close to the observed annual default rate of approximately 0.94 percent and provides a consistent basis for comparing the models. Sensitivity, specificity, and overall classification accuracy are reported to evaluate the tradeoff between identifying defaulting observations and correctly classifying non-defaulting observations. Additional thresholds are examined to assess the sensitivity of classification performance to the selected cutoff. Because default events are relatively infrequent, overall accuracy is considered alongside sensitivity and specificity rather than as the sole measure of predictive performance.

The TTC analysis therefore complements the PIT analysis by evaluating a different dimension of agricultural credit risk. While the PIT models identify borrower financial characteristics, loan characteristics, and repayment history associated with whether a loan experiences default over its observed history, the TTC models use annual loan-year observations to examine the relationships between default and changing economic conditions. The inclusion of contemporaneous and lagged macroeconomic measures allows the analysis to evaluate whether national economic changes and state-level agricultural financial conditions provide additional explanatory or predictive information beyond the borrower and loan characteristics included in the baseline models.

Credit Risk Classification and Scoring

In addition to estimating the probability of default, the PIT analysis develops a credit risk classification system following the methodology established by Featherstone, Roessler, and Barry (2006). While logistic regression provides an estimated probability of default for each loan, translating these probabilities into risk rating classes allows loans to be grouped according to their relative credit risk. This approach provides a framework for evaluating differences in borrower financial characteristics and observed default experience across the loan portfolio. The

classification analysis is restricted to the PIT framework because it produces one predicted probability of default for each individual loan.

Featherstone, Roessler, and Barry (2006) developed a ten class agricultural loan risk rating system using probability of default thresholds derived from historical Standard & Poor's (S&P) credit ratings and KMV estimated default frequencies. Their approach assigned individual loans to risk classes based on estimated default probabilities, with Class 1 representing the lowest risk and Class 10 representing the highest risk. The present analysis adopts the same ten class framework and probability thresholds to maintain methodological consistency with the earlier research. Rather than developing new classification boundaries, the original thresholds are applied to the Farmer Mac loan portfolio to examine their applicability to a different agricultural lending dataset.

The credit risk classification is constructed using the baseline PIT logistic regression model, with default defined as a loan reaching delinquency code 4 or greater during its observed history. The model incorporates the Total Debt Coverage Ratio, Original Loan to Value Ratio, Debt-to-Asset Ratio, and the Log of Loan Amount. Following estimation, the fitted logistic regression coefficients are used to calculate an individual predicted probability of default for each of the 13,967 loans in the PIT sample. The baseline specification is used rather than the farm type or prior delinquency extensions to maintain comparability with the financial characteristics emphasized in the original FRB framework. $RiskClass_i$ is the assigned risk class for loan i, k is the specific risk class between 1 and 10, c_{k-1} is the lower probability threshold, c_k is the upper probability threshold, and PD_i is the loan's predicted probability of default.

$$PIT\ PD_i = \frac{e^{x_i\beta}}{1 + e^{x_i\beta}}$$
$$where\ X_i\beta = \beta_0 + \beta_1 TDC_i + \beta_2 LTV_i + \beta_3 DA_i + \beta_4 ln(LoanAmount_i)$$
$$RiskClass_i = k\ if\ c_{k-1} \leq \widehat{PD}_i \leq c_k$$

Each loan is subsequently assigned to one of the ten risk rating classes using the probability thresholds reported in Table 3.9. The original classification boundaries are retained to provide a consistent benchmark for comparison with the earlier study. Loans with lower predicted probabilities are assigned to lower risk classes, while loans with higher predicted probabilities are assigned to higher risk classes. Because the classification is based on estimated probabilities rather than observed default outcomes, loans are assigned to risk classes independently of whether they ultimately experienced default.

Table 3.9 FRB Risk Rating Classifications

FRB Risk Rating Classification Thresholds	
Risk Class	**Predicted PD Range (%)**
1	0 to <0.035
2	0.035 to <0.080
3	0.080 to <0.140
4	0.140 to <0.260
5	0.260 to <0.520
6	0.520 to <0.690
7	0.690 to <1.145
8	1.145 to <1.730
9	1.730 to <2.880
10	2.880 and above

Source: Featherstone, Roessler, and Barry (2006), Table 8.

Following classification, the number and percentage of loans within each risk class are calculated to examine the distribution of estimated credit risk across the portfolio. Average borrower financial characteristics, including TDC Ratio, Original LTV Ratio, Debt-to-Asset Ratio, and Log Loan Amount, are also summarized by risk class. These comparisons allow the

analysis to examine how differences in repayment capacity, leverage, collateral position, and loan size correspond to the estimated risk classifications.

To evaluate the performance of the classification system, the average predicted probability of default and the observed default rate are calculated for each risk class. The observed default rate is defined as the proportion of loans within a class that reached delinquency code 4 or greater during their observed history. Comparing these measures provides an assessment of whether the estimated probabilities correspond to the actual default experience of loans assigned to each category. Additionally, 95 percent confidence intervals are calculated around the mean predicted probability of default within each class using the sample variation in fitted probabilities. These intervals describe variation in the estimated probabilities within each class but do not account for uncertainty associated with estimation of the underlying logistic regression coefficients.

Predicted and observed default rates are compared across risk classes to evaluate the ability of the classification system to distinguish loans with differing levels of default risk. A useful classification system is expected to exhibit increasing observed default rates as predicted risk increases, although variation may occur in classes containing relatively few loans. Agreement between predicted and observed default rates provides evidence of in-sample calibration, while differences in observed default rates across classes provide information about the model's ability to differentiate levels of credit risk.

Although the classification methodology follows Featherstone, Roessler, and Barry (2006), differences in loan characteristics, default definitions, and observation periods may affect the distribution of loans across risk classes. In particular, the estimated probabilities represent the likelihood of default occurring during each loan's observed history rather than over a

standardized one year period. Consequently, the resulting classifications are interpreted as relative risk groupings within the Farmer Mac portfolio rather than the official S&P credit ratings or independently validated forward looking credit scores. The classification results therefore provide an assessment of the applicability of the historical FRB risk rating framework to the current sample while recognizing the limitations associated with differences in default measurement and observation periods.

Chapter 4 - Results

Point in Time

The baseline model provides an updated comparison with the financial characteristics identified by Featherstone et al. (2006). Repayment capacity has a negative coefficient in the original model, and the corresponding Total Debt Coverage Ratio in this study is also negative and statistically significant. The estimated log odds coefficient of -0.257 indicates that a greater debt servicing capacity is associated with lower default risk which is consistent across the two studies. Owner equity was negative and statistically significant in the original model, indicating that borrowers with greater equity experienced lower default risk. In the present study, Original Loan to Value Ratio is used as a related measure of collateral position. Because a higher Loan to Value Ratio generally indicates lower collateral equity, a positive relationship with default would be expected. However, the estimated coefficient is negative and statistically insignificant, providing little evidence of an independent relationship between Original Loan to Value Ratio and default after controlling for the other financial characteristics.

Debt-to-Asset Ratio used as the corresponding measure for Working Capital, is statistically significant and positive, which is the expected sign, consistent with greater borrower leverage being associated with higher default risk. This is compared with the negative and statistically significant coefficient on working capital in the original model. Finally, commitment amount was not statistically significant in the original Featherstone et al. (2006) model, whereas Log Loan Amount is positive and statistically significant in the current model, indicating that larger loans are associated with higher log odds of default in the Farmer Mac sample after controlling for the other financial characteristics. Overall, the results continue to support the importance of borrower financial condition in predicting agricultural loan default, while also

demonstrating differences in the specific relationships found using a more recent and geographically diverse loan portfolio.

Table 4.1 Baseline FRB Model Log Odds

FRB Variables		Corresponding Variables	
Repayment Capacity	-0.00160	TDC Ratio	-0.25723***
Owner Equity	-0.0316***	Original LTV	-0.28266
Working Capital	-0.00167***	Debt-to-Asset Ratio	2.92720***
Commitment Amount	Not statistically significant	Log Loan Amount	0.28945***
Num Obs	44876	Num Obs	13967
Results are reported in log odds.			

Average marginal effects are also reported to allow the estimated relationships to be interpreted as changes in default probability. Total Debt Coverage Ratio has a negative and statistically significant association with default. The estimated average marginal effect of -0.006 indicates that a one unit increase in Total Debt Coverage Ratio is associated with approximately a 0.6 percentage point decrease in the predicted probability of reaching default, accounting for the other variables included in the model. This relationship is consistent with the expectation that borrowers with greater capacity to service their debt are less likely to experience serious repayment problems.

Debt-to-Asset Ratio exhibits the largest statistically significant financial effect in the baseline specification. A one unit increase in the ratio is associated with a 7.2 percentage point increase in predicted default probability. The positive and statistically significant relationships indicate that more highly leveraged borrowers face greater default risk.

Loan size is also positively associated with default. The average marginal effect for Log Loan Amount is 0.007 and is statistically significant at the one percent level. This suggests that large loans are associated with greater default probability after controlling for borrower repayment capacity, leverage, and collateral position. Original Loan to Value, however, is not

statistically significant in the baseline specification, providing little evidence that it independently predicts default after the other financial characteristics are controlled for.

Table 4.2 Baseline FRB Model AMEs

Baseline Model	
	Average Marginal Effect
Total Debt Coverage Ratio	-0.006***
	(0.002)
Original Loan-to-Value Ratio	-0.007
	(0.009)
Debt-to-Asset Ratio	0.072***
	(0.010)
Log Loan Amount	0.007***
	(0.001)
Observations	13,967
McFadden Pseudo R^2	0.035
Likelihood Ratio χ^2	116.08
AIC	3209.5

Average marginal effects; standard errors in parentheses.
* p < .10; ** p < .05; *** p < .01.

The baseline model has a McFadden pseudo-R^2 of 0.035. This suggests that borrower financial and loan characteristics provide some ability to distinguish defaulting from non-defaulting loans, although substantial variation in default outcomes remains unexplained by the baseline specification.

The relationships identified in the baseline PIT model provide additional evidence supporting the importance of borrower financial characteristics in agricultural credit risk assessment. The findings reinforce the importance of evaluating both a borrower's ability to service debt and overall financial position when assessing agricultural credit risk. However, the lack of statistical significance for Original Loan to Value Ratio in the baseline PIT model suggests that collateral based measures may provide less additional explanatory information once other borrower

financial characteristics are considered. The results therefore support the broader financial risk framework developed by Featherstone, Roessler, and Barry (2006), while demonstrating that the contributions of individual financial measures can differ across loan portfolios and model specifications.

Table 4.3 Farm Type Extension AMEs

Farm Type Extension	
	Average Marginal Effects
Total Debt Coverage Ratio	-0.007***
	(0.002)
Original Loan-to-Value Ratio	-0.008
	(0.009)
Debt-to-Asset Ratio	0.072***
	(0.010)
Log Loan Amount	0.006***
	(0.001)
Livestock	0.007
	(0.004)
Permanent Plantings	0.013***
	(0.005)
Not Specified	-0.026***
	(0.001)
Observations	13,967
McFadden Pseudo R^2	0.039
Likelihood Ratio χ^2	128.89
AIC	3202.7

Average marginal effects; standard errors in parentheses. * p < .10; ** p < .05; *** p < .01. Crops are the omitted category.

The farm type extension examines whether default risk differs across agricultural sectors after controlling for borrower financial condition and loan characteristics. Crop loans serve as the omitted reference category because they represent the largest farm type in the sample. The financial characteristics remain consistent with the baseline model. Total Debt Coverage Ratio

has a negative and statistically significant average marginal effect of -0.007, while Debt-to-Asset Ratio and Log Loan Amount have positive and statistically significant marginal effects of 0.072 and 0.006 respectively. Original Loan to Value Ratio remains statistically insignificant.

Relative to crop loans, permanent planting loans have a positive and statistically significant average marginal effect of 0.013. Holding the other model characteristics constant, this corresponds to an approximately 1.3 percentage point higher predicted probability of reaching default compared with crop loans. The estimated marginal effect for livestock loans is positive at 0.007 but is not statistically significant, indicating that the model does not provide sufficient evidence of a difference in default probability between livestock and crop loans after controlling for the other characteristics. The Not Specified category has a negative and statistically significant marginal effect of -0.026; however, this estimate should be interpreted cautiously because the category contains only 27 loans and no observed defaults.

Overall, incorporating farm type produces only a modest improvement in model fit and discriminatory ability. McFadden's Pseudo-R^2 increases from 0.035 in the baseline model to 0.039 in the farm type model, while AUC increases from 0.658 to 0.664. These results indicate that farm type provides some additional information about default risk, particularly for permanent planting loans, but contributes relatively little additional predictive power beyond the borrower financial and loan characteristics included in the baseline model.

The differences across farm types are also relevant to the findings of Brewer et al. (2012), who applied the Featherstone, Roessler, and Barry (2006) credit risk framework to U.S. agricultural operations and identified variation in estimated default risk across agricultural production sectors. While Brewer et al. found relatively elevated estimated risk among certain livestock operations, the present analysis identifies permanent plantings as having a statistically

significant increase in default probability relative to crop loans, after controlling for borrower financial condition and loan characteristics. These differences may reflect variation in the portfolios, agricultural sectors, and financial measures examined in the two studies. Nevertheless, both analyses indicate that agricultural production type can provide information about credit risk beyond broad measures of borrower financial conditions.

Table 4.4 Prior Delinquency Extension AMEs

Prior Delinquency Extension

	Average Marginal Effects
Total Debt Coverage Ratio	-0.002*
	(0.001)
Original Loan-to-Value Ratio	-0.005
	(0.006)
Debt-to-Asset Ratio	0.009
	(0.006)
Log Loan Amount	0.001
	(0.001)
Prior Early Delinquency	0.576***
	(0.023)
Observations	13,967
McFadden Pseudo R^2	0.663
Likelihood Ratio χ^2	2197.49
AIC	1130.1

Average marginal effects; standard errors in parentheses. * p < .10; ** p < .05; *** p < .01.

Prior repayment behavior provides substantially more information about subsequent default than borrower financial characteristics alone. When an indicator identifying whether a loan previously reached delinquency code 3 or greater is added to the baseline specification, the estimated average marginal effect is 0.576 and is statistically significant at the one percent level. This indicates that loans that previously reached 60-89 days past due have a substantially higher

predicted probability of subsequently reaching the primary default threshold holding the other model characteristics constant.

The inclusion of prior delinquency also substantially improves overall model fit. McFadden's pseudo-R^2 increases from 0.035 in the baseline model to 0.663 in the prior delinquency specification. At the same time, the estimated marginal effects of the baseline financial characteristics become considerably smaller. Total Debt Coverage Ratio remains negative, while Debt-to-Asset Ratio and Log Loan Amount remain positive, but these variables are no longer statistically significant after prior delinquency is included. Original Loan to Value Ratio also remains statistically insignificant. These results suggest that once a borrower begins exhibiting observable repayment difficulties, prior repayment behavior contains information about subsequent default that is not captured by the borrower financial ratios and loan characteristics alone.

Although the inclusion of delinquency history substantially improves model fit and classification performance, these results should be interpreted with caution. The delinquency indicator is constructed using the full observed history of each loan rather than information restricted to a fixed point before default. As a result, the estimated relationship may partly reflect the progression of loans through increasingly severe delinquency categories. The improvement in predictive performance therefore demonstrated the strong association between repayment distress and severe default but should not be interpreted as evidence that the same level of predictive accuracy would be achieved in a prospective lending application.

Taken together, the results demonstrate an important distinction between borrower characteristics that are associated with default risk and repayment behavior that signals progression toward more severe delinquency. Financial characteristics such as repayment

capacity and leverage are significant predictors in the baseline model, but their estimated effects diminish once prior delinquency is observed. Prior delinquency therefore provides substantial additional predictive information for identifying loans that subsequently progress to more severe repayment distress.

Taken together, these results indicate that borrower financial condition remains relevant to agricultural loan default but observed repayment behavior provides substantially greater predictive power once a loan begins exhibiting signs of financial distress.

Classification performance was evaluated across alternative predicted probability cutoffs to determine how effectively the models distinguish between defaulting and non-defaulting loans. Particular attention is given to the 2 percent cutoff to compare with the classification approach used by Featherstone et al. (2006), as well as a 3 percent cutoff to illustrate the tradeoff between sensitivity and specificity as the classification threshold increases.

Table 4.5 PIT Performance 2% Cutoff

Classification Performance of Main Models

Prediction cutoff = 2%

Model	Cutoff	Correct (%)	Sensitivity (%)	Specificity (%)	AUC	TP	FP	TN	FN
Baseline	2%	45.5%	75.0%	44.7%	0.658	267	7,521	6,090	89
Farm Type	2%	46.2%	75.8%	45.4%	0.664	270	7,433	6,178	86
Prior History	2%	98.2%	92.4%	98.4%	0.971	329	218	13,393	27

Correct, sensitivity, and specificity are calculated using a 2% predicted probability cutoff. AUC is the area under the receiver operating characteristic curve. TP = True Positives (defaults correctly classified), TN = True Negatives (non-defaults correctly classified), FP = False Positives (non-defaults incorrectly classified as defaults), FN = False Negatives (defaults incorrectly classified as non-defaults).

At the 2 percent cutoff, the baseline model correctly classifies 45.5 percent of observations, with sensitivity of 75.0 percent and specificity of 44.7 percent. In comparison, the model estimated by Featherstone et al. (2006) correctly classified 91.5 percent of observations, with sensitivity of 21.9 percent and specificity of 92.3 percent. Although the Featherstone et al. (2006) model has substantially higher overall accuracy and specificity, the current model correctly identifies three out of four, compared with approximately one in five in the original model. This

improvement in identifying defaults comes at the cost of substantially higher false positive rate as indicated by the lower specificity.

These differences also illustrate why overall classification accuracy should not be considered independently of sensitivity and specificity. Default is relatively rare in both samples, although the default rate the Farmer Mac sample is slightly higher than in the Featherstone et al. (2006) real estate sample. In the current sample, 2.55 percent of loans reach default, compared with a 1.01 percent default rate among the real estate loans examined by Featherstone et al. (2006). A model can achieve high overall accuracy by correctly classifying the much larger number of non-defaulting loans while still failing to identify many actual defaults.

Adding farm type indicators to the current baseline specification results in only a modest improvement at the 2 percent cutoff. Overall accuracy increases from 45.5 to 46.2 percent, sensitivity increases from 75.0 to 75.8 percent, and specificity increases from 44.7 to 45.4 percent. These results suggest that farm type provides some additional information but does not substantially improve the model's ability to distinguish between defaulting and non-defaulting loans.

In contrast, adding prior delinquency behavior produces a substantial improvement in classification performance. At the 2 percent cutoff, the early delinquency model correctly classifies 98.2 percent of observations, with sensitivity of 92.4 percent and specificity of 98.4 percent. Unlike the baseline and Featherstone et al. (2006) model the early delinquency specification maintains a high ability to correctly identify both defaulting and non-defaulting loans. Its AUC of 0.971, compared with 0.658 for the baseline model and 0.664 for the farm type model provides further evidence of the additional predictive information contained in prior delinquency behavior.

Increasing the probability threshold from 2 to 3 percent changes the classification performance of the baseline and farm type models. For the baseline model, overall accuracy increases from 45.5 to 69.2 percent. Sensitivity decreases from 75.0 to 52.8 percent while specificity increases from 44.7 to 69.6 percent. The farm type model's accuracy increases from 46.2 to 69.8 percent. Sensitivity decreases from 75.8 to 52.0 percent while specificity increases from 45.4 to 70.3 percent. The early delinquency model is considerably less sensitive to this change in cutoff and continues to correctly classify approximately 98 percent of both defaulting and non-defaulting loans.

These results demonstrate that the choice of classification threshold involves an important tradeoff between sensitivity and specificity. A relatively low threshold places greater emphasis on identifying loans that may eventually default but increases the number of performing loans incorrectly classified as risky. Conversely, a higher threshold reduces false positive classifications but increases the likelihood that actual defaults will be missed. For an agricultural lender, the appropriate threshold therefore depends on the relative costs of failing to identify a future default and incorrectly identifying a performing borrower as high risk.

Table 4.6 PIT Performance 3% Cutoff

Classification Performance of Main Models

Prediction cutoff = 3%

Model	Cutoff	Correct (%)	Sensitivity (%)	Specificity (%)	AUC	TP	FP	TN	FN
Baseline	3%	69.2%	52.8%	69.6%	0.658	188	4,139	9,472	168
Farm Type	3%	69.8%	52.0%	70.3%	0.664	185	4,041	9,570	171
Prior History	3%	98.2%	92.4%	98.4%	0.971	329	218	13,393	27

Correct, sensitivity, and specificity are calculated using a 3% predicted probability cutoff. AUC is the area under the receiver operating characteristic curve. TP = True Positives (defaults correctly classified), TN = True Negatives (non-defaults correctly classified), FP = False Positives (non-defaults incorrectly classified as defaults), FN = False Negatives (defaults incorrectly classified as non-defaults).

To evaluate the sensitivity of the PIT results to the definition of default, the models were estimated using delinquency code 3 or greater (60+ days past due) as an alternative to the primary definition of code 4 or greater (90+ days late). This alternative threshold captures loans

experiencing less severe delinquency and allows for an assessment of whether the relationships between borrower financial characteristics and default probability remain consistent across definitions. Table 4.7 presents the average marginal effects for the baseline, farm type, and prior delinquency specifications under both default thresholds.

The baseline results remain largely consistent across the two default definitions, with the total debt coverage ratio maintaining a negative and statistically significant relationship with default probability and the Debt-to-Asset ratio and loan amount maintaining positive and statistically significant relationships. The magnitude of these effects is generally larger under the code 3+ definition, with the marginal effect of the Debt-to-Asset ratio increasing from 0.072 to 0.114 and the marginal effect of log loan amount increasing 0.007 to 0.011. The original loan to value ratio remains statistically insignificant under both definitions. These findings suggest that the primary relationships between borrower financial characteristics and delinquency are not dependent on the selection of the more restrictive default threshold.

The farm type specifications exhibit similar patterns, although some differences emerge across delinquency thresholds. The total debt coverage ratio, Debt-to-Asset ratio, and loan amount retain their direction and statistical significance, while permanent plantings remain positively associated with default probability under both definitions. The livestock indicator becomes statistically significant under the code 3+ definition, while the not specified farm type indicator loses statistical significance. The prior delinquency specifications also demonstrate the importance of delinquency specifications also demonstrate the importance of delinquency history, with the corresponding indicators remaining positive and statistically significant under both thresholds. However, the effects of several financial characteristics are less consistent in

these models, suggesting that delinquency history captures substantial variation in default probability beyond the financial variables alone.

Table 4.7 PIT Robustness Check

PIT Default Definition Robustness Check

Comparison of Default at Delinquency Code 4+ and Code 3+

	Baseline 4+	Baseline 3+	Farm Type 4+	Farm Type 3+	Delinq 4+	Delinq 3+
Total Debt Coverage Ratio	-0.006***	-0.008***	-0.007***	-0.009***	-0.002*	-0.004***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)
Original Loan-to-Value Ratio	-0.007	-0.007	-0.008	-0.007	-0.005	0.002
	(0.009)	(0.011)	(0.009)	(0.011)	(0.006)	(0.008)
Debt-to-Asset Ratio	0.072***	0.114***	0.072***	0.114***	0.009	0.031***
	(0.010)	(0.013)	(0.010)	(0.013)	(0.006)	(0.008)
Log Loan Amount	0.007***	0.011***	0.006***	0.010***	0.001	0.006***
	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)
Livestock			0.007	0.013**		
			(0.004)	(0.006)		
Permanent Plantings			0.013***	0.025***		
			(0.005)	(0.006)		
Not Specified			-0.026***	0.001		
			(0.001)	(0.040)		
Prior Delinquency: Code 3+					0.576***	
					(0.023)	
Prior Delinquency: Code 2+						0.461***
						(0.015)
Observations	13,967	13,967	13,967	13,967	13,967	13,967
McFadden Pseudo R^2	0.035	0.037	0.039	0.042	0.663	0.629
Likelihood Ratio χ^2	116.08	176.75	128.89	202.24	2197.49	3013.69
AIC	3209.5	4621.5	3202.7	4602.1	1130.1	1786.6

Average marginal effects; standard errors in parentheses. * p < .10; ** p < .05; *** p < .01.

Overall, the robustness analysis provides support for the primary PIT findings, particularly the importance of repayment capacity, borrower leverage, and loan size in explaining agricultural loan delinquency. Although some differences arise in the extended specifications, the general consistency of the baseline results indicates that the findings are not driven solely by the choice of delinquency threshold. The code 4+ definition is therefore retained as the primary measure of

default throughout the analysis, while the code 3+ results provide additional evidence regarding the sensitivity of the findings to earlier stages of delinquency.

Through the Cycle

The TTC models examine whether broader economic conditions provide additional information about agricultural loan default after controlling for borrower financial conditions and loan characteristics. Unlike the PIT analysis, which uses one observation per loan, the TTC analysis uses an annual loan-level panel to examine variation in default risk across time. The baseline TTC specification includes the four borrower and loan characteristics used in the baseline PIT model. Subsequent specifications introduce annual CPI Inflation, annual Real GDP Growth, and State Net Cas Farm Income individually, followed by a full specification incorporating all three macroeconomic measures. Default is defined as reaching delinquency code 4 or greater during a given calendar year. The results are reported using logistic regression coefficients and average marginal effects (AMEs), allowing the estimated relationships to be examined in terms of both log odds and changes in predicted default probability.

Total Debt Coverage Ratio maintains a negative and statistically significant relationship with annual default across all five specifications. The estimated coefficient is -0.331 in the baseline model and -0.320 in the full macroeconomic specification. The consistency of this relationship indicates that greater borrower repayment capacity is associated with lower default risk, even after accounting for changes in broader economic conditions.

Original Loan to Value Ratio has a negative estimated coefficient across the TTC specification but is not statistically significant. The baseline coefficient is -0.168, compared with -0.174 in the full model. Although the negative direction differs from the expected positive relationship between collateral leverage and default risk, the lack of statistical significance

provides insufficient evidence of an independent relationships between Original Loan to Value Ratio and annual default after controlling for the other financial and macroeconomic characteristics.

Debt-to-Asset Ratio is positively and statistically significant associated with default across all specifications. In the baseline model, the coefficient is 2.754 and 2.685 in the full specification. These results indicate that greater borrower leverage is consistently associated with higher annual default risk. The stability of the estimated relationship after incorporating macroeconomic conditions suggest that borrower financial position remains an important indicator of agricultural loan default risk.

Log Loan Amount similarly maintains a positive and statistically significant relationship with default across all specifications. The estimated coefficient increased slightly from 0.394 in the baseline model to 0.408 in the full model. These findings suggest that larger loans are associated with greater annual default risk after controlling for borrower repayment capacity, leverage, collateral position, and broader economic conditions.

Overall, the estimated relationships between borrower financial characteristics and default remain relatively stable as macroeconomic variables are introduced. Total Debt Coverage Ratio, Debt-to-Asset Ratio, and Log Loan Amount maintain their directions and statistical significance, while Original Loan to Value Ratio remains statistically insignificant. These findings indicate that borrower level financial conditions continue to provide important information about agricultural loan default risk within the annual TTC framework.

Table 4.8 TTC AMEs

Through the Cycle Regression Results

Variable	Baseline	+ CPI	+ GDP	+ State NCFI	Full
Total Debt Coverage Ratio — Logit	-0.3309*** (0.0471)	-0.3344*** (0.0472)	-0.3293*** (0.0470)	-0.3191*** (0.0470)	-0.3198*** (0.0471)
Total Debt Coverage Ratio — AME	-0.003074*** (0.000450)	-0.003106*** (0.000451)	-0.003058*** (0.000449)	-0.002963*** (0.000448)	-0.002970*** (0.000449)
Original Loan-to-Value Ratio — Logit	-0.1680 (0.2438)	-0.1657 (0.2442)	-0.1746 (0.2440)	-0.1688 (0.2450)	-0.1736 (0.2453)
Original Loan-to-Value Ratio — AME	-0.001560 (0.002265)	-0.001539 (0.002268)	-0.001622 (0.002266)	-0.001567 (0.002276)	-0.001612 (0.002278)
Debt-to-Asset Ratio — Logit	2.7536*** (0.2697)	2.7171*** (0.2709)	2.7313*** (0.2700)	2.7153*** (0.2701)	2.6853*** (0.2709)
Debt-to-Asset Ratio — AME	0.025576*** (0.002653)	0.025235*** (0.002660)	0.025365*** (0.002653)	0.025215*** (0.002652)	0.024933*** (0.002656)
Log Loan Amount — Logit	0.3937*** (0.0367)	0.4021*** (0.0369)	0.3983*** (0.0367)	0.4017*** (0.0367)	0.4084*** (0.0369)
Log Loan Amount — AME	0.003657*** (0.000362)	0.003734*** (0.000366)	0.003699*** (0.000363)	0.003731*** (0.000364)	0.003792*** (0.000366)
CPI Inflation — Logit		-0.0423** (0.0195)			-0.0173 (0.0214)
CPI Inflation — AME		-0.000393** (0.000181)			-0.000161 (0.000198)
Real GDP Growth — Logit			-0.0488*** (0.0180)		-0.0397** (0.0200)
Real GDP Growth — AME			-0.000453*** (0.000168)		-0.000369** (0.000186)
State Net Cash Farm Income ($ Billion) — Logit				-0.0175*** (0.0059)	-0.0162*** (0.0059)
State Net Cash Farm Income ($ Billion) — AME				-0.000162*** (0.000055)	-0.000150*** (0.000055)
Observations	83,052	83,052	83,052	83,052	83,052
McFadden Pseudo R^2	0.035	0.035	0.036	0.036	0.037
Likelihood Ratio Chi^2	307.19	312.08	314.35	316.38	323.55
AIC	8556.06	8553.17	8550.90	8548.87	8545.70

Dependent variable: default at delinquency Code 4+. Logit coefficients and average marginal effects (AMEs) are shown with conventional standard errors in parentheses. AMEs are probability changes per one-unit increase in the predictor. * p < .10; ** p < .05; *** p < .01.

The macroeconomic extensions examine whether changes in broader economic conditions are associated with default probability beyond the borrower and loan characteristics included in the baseline model. When introduced individually, annual CPI Inflation, annual Real GDP Growth, and State Net Cash Farm Income the estimated relationships provide evidence of

how national economic conditions and state level agricultural income are associated with default risk.

Annual CPI Inflation exhibits a negative relationship with default when introduced individually. The estimated logistic regression coefficient is -0.042 and is statistically significant at the ten percent level. This suggests that higher annual inflation is associated with lower default risk in the individual CPI specification, conditional on the borrower and loan characteristics. However, the estimated coefficient decreases in magnitude to -0.017 and becomes statistically insignificant in the full model. This change indicates that the relationships between inflation and default is sensitive to the inclusion of other macroeconomic measures and does not provide strong evidence of an independent association after accounting for Real GDP Growth and State NCFI.

Annual Real GDP Growth is also negatively associated with default probability. The individual GDP specification produces an estimated coefficient of -0.049, which is statistically significant at the five percent level. In the full specification, the coefficient remains negative at -0.040 and is statistically significant at the ten percent level. These results suggest that stronger national economic growth is associated with lower agricultural loan default risk, although the weaker statistically significance in the full model indicates that the relationship should be interpreted cautiously.

State NCFI exhibits a negative and statistically significant relationship with default in both the individual and full specifications. The estimated coefficient is -0.017 in the individual model and -0.016 in the full model, with both estimates statistically significant at the five percent level. Because State NCFI is measured in billions of dollars, these coefficients describe the changes in the log odds of default associated with a $1 billion increase in state agricultural

income. The consistent negative relationship suggests that stronger agricultural income conditions at the state level are associated with lower annual loan default risk, even after controlling for borrower characteristics and national macroeconomic conditions.

When all three macroeconomic variables are included simultaneously, Real GDP Growth and State NCFI remain negatively associated with default and statistically significant, while CPI Inflation is no longer statistically significant. These findings suggest that measures of national economic growth and state-level agricultural income provide more consistent additional information about default risk than inflation within the specifications examined. However, the results represent conditional statistical associations rather than causal effects of macroeconomic conditions on agricultural loan performance.

The inclusion of macroeconomic variables produces a modest improvement in overall model fit and discriminatory ability. McFadden's pseudo-R^2 increases from 0.035 in the baseline TTC specification to 0.037 in the full macroeconomic model. Similarly, the area under the receiver operating characteristic curve increases from 0.673 for the baseline model to 0.677 for the full specification. Although these improvements are relatively small, they suggest that macroeconomic conditions provide some additional information about annual agricultural loan default beyond the borrower financial and loan characteristics included in the baseline model. The limited magnitude of the improvement also indicates that substantial variation in default outcomes remains unexplained by the specification examined.

The predictive performance of the TTC models was evaluated using sensitivity, specificity, overall classification accuracy, and the area under the receiver operating characteristics (AUC). Because the TTC analysis uses annual loan-year observations, the observed default rate differs from the loan-level default rate in the PIT analysis. Of the 83,052

loan-year observations included in the TTC models, 782 are classified as defaults, representing approximately 0.94 percent of observations. A predicted probability cutoff of 0.90 percent was selected for the classification analysis. This threshold is close to the observed annual default rate and provides a common basis for comparing classification performance across the five TTC specifications.

At the 0.90 percent cutoff, classification performance is relatively consistent across the TTC specifications. The baseline model correctly classifies 58.6 percent of observations, with a sensitivity of 64.2 percent and specificity of 58.5 percent. Adding individual macroeconomic variables produces relatively small changes in classification performance. The CPI Inflation model achieves 58.5 percent accuracy and 64.8 percent sensitivity, while the Real GDP Growth model achieves 58.7 percent accuracy and 65.3 percent sensitivity. The State NCFI model achieves 58.9 percent accuracy and 66.1 percent sensitivity, representing the highest sensitivity among the five specifications.

The full TTC model produces the highest overall classification accuracy and AUC among the specifications examined. At the selected cutoff, the full model correctly classifies 59.0 percent of loan-year observations, identifies 66.0 percent of actual default observations, and correctly classifies 58.9 percent of nondefault observations. Its AUC is 0.677, compared with 0.673 for the baseline model. Although the inclusion of macroeconomic variables modestly improves discriminatory ability, the relatively small increase in AUC indicates that these variables provide limited additional predictive information beyond the borrower financial and loan characteristics included in the baseline specification.

Table 4.9 TTC Performance 0.90% Cutoff

Classification Performance of TTC Models

Prediction cutoff = 0905%

Model	Correct (%)	Sensitivity (%)	Specificity (%)	AUC
Baseline	58.6	64.2	58.5	0.673
+ CPI	58.5	64.8	58.4	0.674
+ GDP	58.7	65.3	58.6	0.674
+ State NCFI	58.9	66.1	58.8	0.676
Full	59.0	66.0	58.9	0.677

Default at Code 4+; classification cutoff = 0.90% predicted probability. AUC = area under the ROC curve.

The relatively modest improvement in predictive performance from incorporating macroeconomic variables is consistent with the findings of Johnson, Boehlje, and Gunderson (2017). Their analysis of agricultural borrower risk rating migration found that farm-level and agricultural sector financial measures were generally more reliable predictors of changes in borrower credit risk that broader macroeconomic variables. Similarly, the present study finds that borrower repayment capacity, leverage, and loan size maintain consistent relationships with annual default after national and state-level economic conditions are incorporated. Although Real GDP Growth and State NCFI are statistically significant in the full TTC specification, the increase in AUC from 0.673 in the baseline model to 0.677 in the full model indicates that their additional contribution to discrimination is limited. These findings suggest that macroeconomic conditions provide useful supplementary information about the environment in which agricultural loans perform, but do not replace the importance of borrower specific financial characteristics. An important distinction between the studies is that Johnson, Boehlje, and Gunderson examined changes in borrower risk ratings among grain farms, whereas the present analysis evaluates observed delinquency based default across a broader agricultural real estate loan portfolio.

To evaluate the sensitivity of the TTC results to the definition of default the five specifications were reestimated using delinquency code 3 or greater (60 or more days past due) as an alternative to the primary definition of code 4 or greater (90 or more days past due). The annual default indicator identifies whether a loan reached the applicable delinquency threshold at any point during the calendar year. This alternative threshold captures earlier stages of repayment distress and allows the analysis to examine whether the relationships between borrower financial characteristics, macroeconomic conditions, and default remain consistent when less severe delinquency is included. Table 4.10 presents the logistic regression coefficients for the baseline, individual, macroeconomic, and full macroeconomic specifications under both default definitions.

Table 4.10 TTC Robustness Check

Through the Cycle Default Definition Robustness Check

Variable	Baseline 4+	Baseline 3+	CPI 4+	CPI 3+	GDP 4+	GDP 3+	NCFI 4+	NCFI 3+	Full 4+	Full 3+
Total Debt Coverage Ratio	-0.331***	-0.308***	-0.334***	-0.311***	-0.329***	-0.307***	-0.319***	-0.301***	-0.320***	-0.303***
	(0.047)	(0.038)	(0.047)	(0.038)	(0.047)	(0.038)	(0.047)	(0.038)	(0.047)	(0.038)
Original Loan-to-Value Ratio	-0.168	-0.028	-0.166	-0.026	-0.175	-0.033	-0.169	-0.028	-0.174	-0.029
	(0.244)	(0.201)	(0.244)	(0.202)	(0.244)	(0.201)	(0.245)	(0.202)	(0.245)	(0.202)
Debt-to-Asset Ratio	2.754***	2.648***	2.717***	2.615***	2.731***	2.633***	2.715***	2.626***	2.685***	2.597***
	(0.270)	(0.221)	(0.271)	(0.222)	(0.270)	(0.221)	(0.270)	(0.221)	(0.271)	(0.222)
Log Loan Amount	0.394***	0.378***	0.402***	0.385***	0.398***	0.381***	0.402***	0.383***	0.408***	0.389***
	(0.037)	(0.030)	(0.037)	(0.030)	(0.037)	(0.030)	(0.037)	(0.030)	(0.037)	(0.031)
Annual CPI Inflation (%)			-0.042**	-0.038**					-0.017	-0.024
			(0.019)	(0.016)					(0.021)	(0.018)
Annual Real GDP Growth (%)					-0.049***	-0.034**			-0.040**	-0.023
					(0.018)	(0.015)			(0.020)	(0.017)
State Net Cash Farm Income ($ Billions)							-0.017***	-0.011**	-0.016***	-0.009*
							(0.006)	(0.005)	(0.006)	(0.005)
Observations	83,052	83,052	83,052	83,052	83,052	83,052	83,052	83,052	83,052	83,052
McFadden Pseudo R^2	0.035	0.035	0.035	0.035	0.036	0.035	0.036	0.035	0.037	0.035
Likelihood Ratio Chi^2	307.19	422.38	312.08	428.20	314.35	427.36	316.38	427.50	323.55	433.92
AIC	8,556.1	11,825.7	8,553.2	11,821.9	8,550.9	11,822.7	8,548.9	11,822.6	8,545.7	11,820.2

Logit coefficients with conventional standard errors in parentheses. 4+ and 3+ refer to the delinquency-code default definitions. * p < .10; ** p < .05; *** p < .01.

The borrower financial characteristics exhibit consistent relationships across the two default thresholds. Total Debt Coverage Ratio remains negative and statistically significant across all five specifications under both definitions. In the baseline model, its estimated coefficient changes from -0.331 under code 4+ to -0.308 under code 3+, while the corresponding full model coefficients are -0.320 and -0.303. These findings suggest that greater borrower repayment capacity is consistently associated with lower default risk, regardless of whether the outcome includes delinquency beginning at 60 or 90 days past due.

Original Loan to Value Ratio maintains a negative estimated coefficient across all specifications under both default definitions but is not statistically significant. In the baseline model, the coefficient changes from -0.168 under code 4+ to -0.028 under code 3+, while the full model coefficients are -0.174 and -0.029, respectively. The lack of statistical significance indicates that the analysis does not provide sufficient evidence of an independent relationships between Original Loan to Value Ratio and annual default after controlling for the other borrower and loan characteristics.

Debt-to-Asset Ratio and Log Loan Amount maintain positive and statistically significant relationships with default under both thresholds. In the baseline models, the Debt-to-Asset Ratio coefficient decreases from 2.754 under code 4+ to 2.648 under code 3+, while Log Loan Amount decreases from 0.394 to 0.378. Similar relationships are observed in the full specifications. These findings indicate that greater borrower leverage and larger loan amounts are consistently associated with higher annual default risk, even when the default definition is broadened to include earlier stages of repayment distress.

The macroeconomic variables demonstrate somewhat greater sensitivity to the definition of default. When introduced individually, annual CPI Inflation remains negative and statistically

significant at the five percent level under both thresholds, with coefficients of -0.042 under code 4+ and -0.038 under code 3+. Annual Real GDP Growth also maintains a negative and statistically significant relationship in its individual specifications, although its coefficient decreases in magnitude from -0.049 under code 4+ to -0.034 under code 3+. State NCFI remains negatively associated with default in both individual specifications, with coefficients of -0.017 and -0.011, respectively. These results suggest that stronger national economic growth and state-level agricultural income conditions are associated with lower default risk under both definitions when the macroeconomic measures are examined individually.

In the full macroeconomic specification, the estimated relationships are less consistent across default definitions. CPI Inflation remains negative but statistically insignificant under both thresholds, with coefficients of -0.017 under code 4+ and -0.024 under code 3+. Real GDP Growth is negative and statistically significant at the five percent level under code 4+, with a coefficient of -0.040, but becomes statistically insignificant under code 3+, with a coefficient of -0.023. State NCFI remains negative and statistically significant under both definitions, although its coefficient decreases in magnitude from -0.016 under code 4+ to -0.009 under code 3+, and its significance weakens form the one percent level to the ten percent level. These findings indicate that the relationships between macroeconomic conditions and annual default are somewhat sensitive to the severity of delinquency used to define the outcome.

Overall, the TTC robustness analysis provides support for the primary findings concerning borrower financial characteristics. Total Debt Coverage Ratio, Debt-to-Asset Ratio, and Log Loan Amount maintain consistent directions and statistical significance across both default definitions, while Original Loan to Value Ratio remains statistically insignificant. The macroeconomic findings are less robust, particularly in the full specifications, where Real GDP

Growth loses statistical significance under the broader code 3+ threshold. Nevertheless, State NCFI maintains a negative association with default under both definitions. These results suggest that borrower financial condition provides a relatively stable basis for understanding agricultural loan default risk, while the estimated relationships with broader economic conditions depend partly on the severity of delinquency being examined.

To further examine the relationship between broader economic conditions and agricultural loan default, additional TTC specifications were estimated using one-year lagged macroeconomic variables. These models incorporate annual CPI inflation, Real GDP growth, and State Net Cash Farm Income from the preceding calendar year rather than the current year. The purpose of this extension is to examine whether economic conditions observed in the previous year are associated with default during the subsequent year. The borrower financial and loan characteristics included in the baseline TTC specification remain unchanged, and default continues to be defined as reaching delinquency code 4 or greater during the calendar year. The lagged analysis includes 82,652 loan-year observations.

The borrower financial characteristics maintain relationships with default that are consistent with the contemporaneous TTC specifications. Total Debt Coverage Ratio remains negative and statistically significant across all four lagged models, with coefficients ranging from −0.337 to −0.315. Debt-to-Asset Ratio and Log Loan Amount maintain positive and statistically significant relationships, while Original Loan-to-Value Ratio remains statistically insignificant. These findings suggest that the relationships between borrower financial condition and default remain relatively stable when macroeconomic conditions are measured using values from the preceding year.

Lagged CPI inflation exhibits a negative relationship with default. When introduced individually, the estimated logistic regression coefficient is −0.042 and is statistically significant at the ten percent level. In the full lagged specification, the coefficient remains negative at −0.037 and is also significant at the ten percent level. These findings suggest that higher inflation in the preceding year is associated with lower current-year default risk, although the relatively weak statistical significance warrants cautious interpretation.

Lagged Real GDP growth does not exhibit a statistically significant relationship with default in either specification. The individual lagged GDP model produces an estimated coefficient of −0.006, while the full lagged model produces a coefficient of 0.013. Neither estimate is statistically significant. This contrasts with the contemporaneous TTC results, in which current-year GDP growth maintains a negative and statistically significant relationship with default. The difference suggests that the estimated association between national economic growth and agricultural loan default depends partly on the timing of the economic measure.

Lagged State Net Cash Farm Income maintains a negative and statistically significant relationship with default. The estimated coefficient is −0.026 in the individual specification and −0.024 in the full specification, both statistically significant at the one percent level. These results indicate that stronger state-level agricultural income conditions in the preceding year are associated with lower current-year default risk after controlling for borrower financial characteristics and other lagged macroeconomic variables. The consistency of this negative relationship across contemporaneous and lagged specifications suggests that state-level agricultural income provides relatively stable information about agricultural loan default risk.

Overall, the lagged macroeconomic analysis provides additional evidence that the timing of economic conditions matters when evaluating agricultural loan default. State Net Cash Farm

Income maintains a negative and statistically significant association with default across both contemporaneous and lagged specifications, while Real GDP growth is significant only when measured contemporaneously. Lagged CPI inflation is negatively associated with default, although its statistical significance is relatively weak. These findings suggest that economic conditions from the preceding year may provide supplementary information about current-year loan performance, particularly through state-level agricultural income measures. However, the estimates should be interpreted as statistical associations rather than evidence of causal relationships.

Table 4.11 TTC Lagged Regression Results

Lagged Macroeconomic Variables Results				
Variable	**CPI Lag**	**GDP Lag**	**State NCFI Lag**	**Full Lag**
Total Debt Coverage Ratio	-0.337*** (0.047)	-0.333*** (0.047)	-0.315*** (0.047)	-0.320*** (0.047)
Original Loan-to-Value Ratio	-0.145 (0.244)	-0.154 (0.244)	-0.158 (0.246)	-0.148 (0.246)
Debt-to-Asset Ratio	2.721*** (0.271)	2.745*** (0.270)	2.689*** (0.271)	2.672*** (0.271)
Log Loan Amount	0.399*** (0.037)	0.393*** (0.037)	0.404*** (0.037)	0.409*** (0.037)
CPI Inflation (t-1)	-0.042* (0.020)			-0.037* (0.022)
Real GDP Growth (t-1)		-0.006 (0.019)		0.013 (0.021)
State Net Cash Farm Income ($ Billion) (t-1)			-0.026*** (0.006)	-0.024*** (0.006)
Observations	82,652	82,652	82,652	82,652
McFadden Pseudo R^2	0.035	0.035	0.037	0.037
Likelihood Ratio Chi^2	310.92	306.30	325.24	328.22

Standard errors in parentheses. * p < .10; ** p < .05; *** p < .01.

Taken together, the TTC results indicate that borrower financial condition and loan characteristics remain important components of agricultural default risk when broader economic conditions are considered. Greater repayment capacity is consistently associated with lower default risk, while higher borrower leverage and larger loan amounts are associated with

increased default risk. These relationships remain stable across the contemporaneous and lagged macroeconomic specifications and under alternative delinquency-based default definitions. Original Loan to Value Ratio, however, does not exhibit a statistically significant relationship with default in the annual TTC models.

Macroeconomic conditions provide additional information about agricultural loan performance, although their estimated relationships vary across specifications. Contemporaneous Real GDP Growth and State NCFI are negatively associated with default in the full model, while CPI Inflation is not statistically significant. In the lagged specifications, State NCFI maintains a negative and statistically significant relationship with default, whereas Real GDP Growth is no longer statistically significant. The robustness analysis also indicates that the statistical significance of some macroeconomic relationships weakens when the default threshold is lowered from code 4+ to code 3+. These findings suggest that the relationship between macroeconomic conditions and agricultural loan default depends partly on the timing of economic measures and the severity of delinquency being examined.

Despite the statistically significant relationships identified in several specifications, incorporating macroeconomic variables produces only modest improvements in model fit and discrimination. The AUC increases from 0.673 in the baseline TTC model to 0.677 in the full contemporaneous specification, while classification accuracy increases from 58.6 percent to 59.0 percent at the selected 0.90 percent probability cutoff. These results suggest that macroeconomic conditions supplement borrower-level financial information without substantially improving the overall discriminatory ability of the TTC models.

The consistency of borrower financial characteristics across the TTC specifications is also related to the findings of Featherstone, Wilson, and Zollinger (2017), who examined the

ability of financial measures to predict agricultural borrower risk ratings over different time horizons. Their analysis identified borrower financial condition, particularly leverage, as an important predictor of subsequent risk ratings, although the usefulness of individual financial measures varied across prediction horizons. The present study similarly finds that Debt-to-Asset Ratio maintains a positive and statistically significant relationship with default across the annual TTC specifications, including models incorporating contemporaneous and lagged macroeconomic conditions and alternative delinquency based default definitions. While the two studies examine different outcomes and time horizons, their findings reinforce the importance of borrower financial strength in evaluating agricultural credit risk. The TTC results further indicate that broader economic conditions, particularly state-level agricultural income, can supplement borrower-level financial information, although their contribution to overall model discrimination remains modest.

PIT vs TTC Comparison

The Point in Time (PIT) and Through the Cycle (TTC) analyses provide complementary evidence about agricultural loan default risk. Both approaches identify borrower financial condition and loan characteristics as important factors associated with default. Greater repayment capacity, measured by Total Debt Coverage Ratio, is associated with lower default risk, while greater borrower leverage and larger loan amounts are associated with higher default risk. These relationships remain generally consistent across the two approaches, suggesting that the financial characteristics emphasized in the original Featherstone, Roessler, and Barry (2006) framework continue to provide useful information for evaluating agricultural credit risk.

The PIT analysis focuses on differences across individual loans by evaluating whether each loan reaches the specified default threshold at any point during its observed history. The

baseline model demonstrates that borrower financial characteristics and loan size are associated with default, while the farm type extension provides a modest improvement in model performance. Permanent planting loans exhibit higher estimated default risk relative to crop loans after controlling for borrower and loan characteristics. The delinquency extension demonstrates a particularly strong association between repayment distress and more severe default. However, because the delinquency indicator is constructed using information from each loan's observed history, including information that may occur at or after default, these results should be interpreted as retrospective associations rather than evidence of prospective predictive performance.

The TTC analysis extends the baseline framework by retaining annual loan-year observations and incorporating changing national and state-level economic conditions. The relationships between borrower financial characteristics and default remain generally consistent when macroeconomic measures are included. Contemporaneous Real GDP Growth and State NCFI exhibit negative and statistically significant relationships with default in the full specification, while CPI Inflation is not statistically significant. The lagged analysis further indicates that State NCFI maintains a negative and statistically significant relationship with default when measured using the preceding year's economic conditions. These findings suggest that broader economic conditions provide additional information about agricultural loan default risk, although the strength of individual relationships varies with the timing of the economic measures.

The predictive results further illustrate the different contributions of the model extensions. In the PIT analysis, the baseline model produces an AUC of 0.658, compared with 0.664 for the farm type extension. Incorporating the delinquency history indicator increases the

AUC to 0.971, reflecting the strong in-sample association between repayment distress and severe default. However, the construction of this indicator limits its usefulness for prospective prediction. In the TTC analysis, the AUC increases from 0.673 in the baseline model to 0.677 in the full contemporaneous macroeconomic specification. Classification accuracy at the selected 0.90 percent cutoff also improves only modestly, increasing from 58.6 percent to 59.0 percent. These results indicate that incorporating macroeconomic conditions provides relatively limited improvements in discrimination compared with the baseline TTC model.

An important distinction between the two approaches is the definition and timing of the default outcome. The PIT models use one observation per loan and identify whether a loan reaches default during its observed history, while the TTC models evaluate whether a loan reaches default during each calendar year. Consequently, the two analyses have different observed default frequencies and prediction horizons. The PIT sample has an observed default rate of approximately 2.55 percent, compared with approximately 0.94 percent of loan-year observations in the TTC sample. Because the units of observation and outcome horizons differ, the predictive performance statistics are not directly comparable. Instead, comparisons are most informative within each framework, where model extensions can be evaluated against their respective baseline specifications.

The comparison between the PIT and TTC approaches also extends previous agricultural credit risk research by examining borrower financial characteristics and macroeconomic conditions within two complementary modeling frameworks. Featherstone, Roessler, and Barry (2006) demonstrated the usefulness of borrower financial ratios for estimating agricultural loan default probabilities, while Johnson, Boehlje, and Gunderson (2017) examined how borrower, agricultural sector, and macroeconomic characteristics relate to changes in agricultural credit risk

ratings. The present study builds on these approaches by evaluating observed delinquency-based default using both a loan-level PIT framework and an annual loan-year TTC framework. The consistency of repayment capacity, leverage, and loan amount across the two approaches reinforces the importance of borrower financial condition identified in earlier research. At the same time, the TTC results indicate that broader economic conditions provide additional information about default risk, particularly through state-level agricultural income measures.

Taken together, the PIT and TTC results indicate that borrower financial condition provides a foundation for evaluating agricultural loan default risk, while repayment behavior and macroeconomic conditions contribute different types of additional information. Delinquency history is strongly associated with severe repayment distress within the PIT analysis, although its retrospective construction limits its prospective interpretation. Macroeconomic conditions provide additional context for annual default risk without substantially improving the discriminatory ability of the TTC models. These findings support the importance of borrower and loan characteristics in agricultural credit risk assessment while highlighting the complementary roles of repayment behavior and broader economic conditions.

Credit Risk Classification

The credit risk classification system was applied to the 13,967 loans in the PIT sample using predicted probabilities of default from the baseline FRB model. The average predicted probability of default was 2.55 percent, corresponding to the observed default rate in the sample. Individual predicted probabilities ranged from 0.12 percent to 14.93 percent, indicating considerable variation in estimated credit risk across the portfolio. Following the classification thresholds established by Featherstone, Roessler, and Barry (2006), each loan was assigned to one of ten risk rating classes, with higher classes representing greater estimated default risk.

The distribution of loans across the ten risk classes was concentrated in the higher categories. As shown in Table 4.12, no loans were assigned to classes 1 or 2, while only 350 loans, representing approximately 2.51 percent of the portfolio, were assigned to classes 3 through 5. Classes 9 and 10 contained 4,248 and 4,697 loans, respectively, accounting for approximately 64.04 percent of the portfolio. This concentration indicates that the historical FRB classification thresholds place a substantial proportion of the Farmer Mac portfolio within higher risk categories. However, differences in default definitions, observation periods, and portfolio characteristics limit direct comparisons with the original FRB study.

Table 4.12 Loans by Risk Rating Class

Characteristics of Loans by Risk Rating Class

Risk Class	TDC Ratio	Original LTV (%)	Debt-to-Asset (%)	Loan Amount ($1,000)	Actual Default (%)	Lower 95% CI	Predicted PD (%)	Upper 95% CI	Loans	Portfolio (%)
1	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	0	0.00
2	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	0	0.00
3	8.22	50.71	6.44	83.42	0.00	0.128	0.131	0.135	9	0.06
4	7.97	48.33	9.76	277.52	0.00	0.199	0.206	0.213	100	0.72
5	6.35	46.38	14.35	500.57	0.41	0.384	0.394	0.403	241	1.73
6	4.49	47.15	15.38	376.53	0.00	0.599	0.606	0.613	196	1.40
7	2.29	43.44	12.43	317.37	1.40	0.960	0.968	0.975	1,215	8.70
8	1.18	43.14	11.87	411.90	1.59	1.432	1.438	1.444	3,261	23.35
9	1.59	45.02	27.97	648.47	2.05	2.260	2.270	2.280	4,248	30.41
10	1.43	46.89	40.34	1,566.46	4.24	4.192	4.228	4.264	4,697	33.63

Confidence Intervals describe the mean fitted PD within each class, not uncertainty from estimation of regression coefficients. N/A indicates a class with no observations.

The financial characteristics of loans also varied across risk classes. Average Total Debt Coverage Ratio generally declined as predicted default risk increased, falling from 8.22 in Class 3 to 1.43 in Class 10. Debt-to-Asset ratio exhibited the opposite pattern, increasing from 6.44% in class 3 to 40.34% in class 10. Average loan amounts were also substantially higher in the

upper risk categories, reaching $1.57 million in class 10 compared with approximately $83,420 in class 3. Original Loan to Value ratios displayed less consistent variation across classes, ranging from 43% to 51%. These patterns are consistent with the baseline PIT regression results, which identified repayment capacity, leverage, and loan size as important characteristics associated with agricultural loan default.

Comparisons between predicted and observed default rates provide additional evidence of risk differentiation and in-sample calibration across the classification system. Observed default rates generally increased across the higher risk classes, rising from 1.40 percent in Class 7 to 1.59 percent in Class 8, 2.05 percent in Class 9, and 4.24 percent in Class 10. The corresponding average predicted default probabilities were 0.97 percent, 1.44 percent, 2.27 percent, and 4.23 percent, respectively. The relatively close agreement between predicted and observed default rates in the largest classes suggests that the baseline model provides reasonable in-sample calibration across the higher-risk portion of the portfolio. However, these results do not establish that the model would maintain similar calibration when applied to loans outside the estimation sample.

Greater variation between predicted and observed default rates occurred in the lower risk classes. Classes 3, 4, and 6 recorded no observed defaults, while class 5 has an observed default rate of 0.41%. These differences should be interpreted cautiously because the lower risk classes contain relatively few loans, making their observed default rates more sensitive to individual outcomes. For example, class 3 contained only nine loans while class 4 contained 100. The absence of observed defaults in these categories therefore does not necessarily indicate that the model systematically overestimates default risk.

Figure 4.1 Actual and Predicted Default Rates by Risk Rating Class

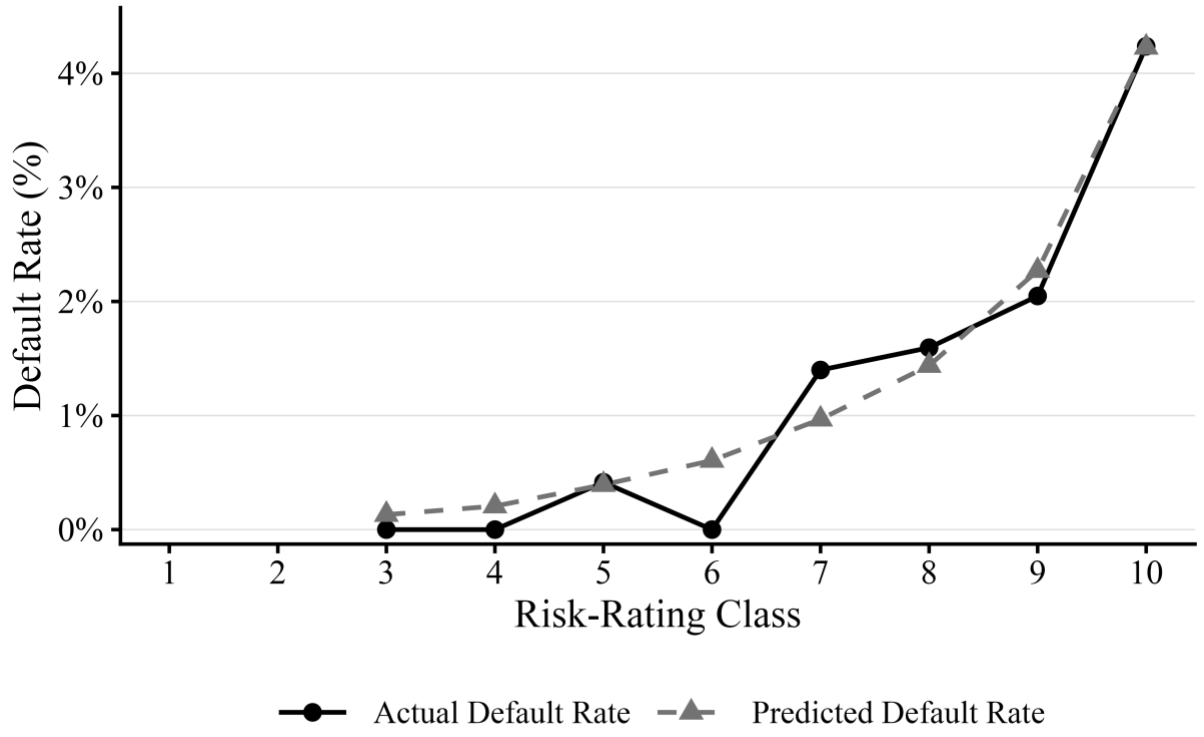


Figure 4.1 illustrates the relationship between predicted and observed default rates across the risk classes. Although the observed rates do not increase uniformly across every category, the general upward pattern indicates that the classification system distinguishes among loans with different levels of default risk. The relatively close agreement between predicted and observed default rates in classes 8 through 10 further supports the usefulness of the baseline model for differentiating risk within the Farmer Mac portfolio. However, these comparisons are based on the estimation sample and do not establish how well the model would perform when applied to new loans.

Although the classification results demonstrate differences in estimated credit risk across the portfolio, the assigned classes should not be interpreted as equivalent to official Standard & Poor's credit ratings. The classification thresholds were adopted from Featherstone, Roessler,

and Barry (2006), while the predicted probabilities in the present study represent the likelihood of reaching the specified default threshold during each loan's observed history. Because observation periods vary across loans and do not correspond to a standardized one year default horizon, the resulting classifications are best interpreted as relative risk groupings within the Farmer Mac portfolio. Furthermore, the comparison of predicted and observed default rates provides evidence of in-sample calibration rather than independently validated predictive performance. Additional out of sample validation would be necessary before applying the classification system prospectively.

Overall, the credit risk classification results suggest that the baseline PIT model provides a useful framework for differentiating agricultural loans according to estimated default risk. Loans assigned to higher risk classes generally exhibit weaker repayment capacity, greater leverage, and larger loan amounts, consistent with the relationships identified in the logistic regression analysis. The classification system also demonstrates reasonable agreement between predicted and observed default rates in the largest risk categories, although these findings reflect in-sample performance. Together, these results support the continued relevance of the borrower financial characteristics emphasized by Featherstone, Roessler, and Barry (2006), while highlighting the importance of evaluating historical risk classification thresholds within the context of the current lending portfolio. The findings also demonstrate the potential usefulness of translating estimated default probabilities into relative risk categories, provided that differences in default horizons, portfolio characteristics, and validation requirements are recognized.

Chapter 5 - Conclusion

This study examined the probability of default in agricultural real estate loans using data from the Federal Agricultural Mortgage Corporation (Farmer Mac). Building on the framework developed by Featherstone, Roessler, and Barry (2006), the analysis sought to evaluate whether borrower financial characteristics identified in earlier agricultural credit risk research remain important in a more recent and geographically diverse loan portfolio. The study also examined whether farm type, repayment history, and broader economic conditions provide additional information about agricultural loan default. To address these objectives, PIT and TTC logistic regression models were estimated, and predicted default probabilities from the baseline PIT model were used to construct a ten class credit risk classification system.

The PIT analysis, based on 13,967 individual agricultural real estate loans, identified borrower repayment capacity, leverage, and loan amount as important characteristics associated with default. Greater Total Debt Coverage Ratio was associated with a lower probability of default, while higher Debt-to-Asset Ratio and larger loan amounts were associated with greater default risk. These relationships were generally consistent with the financial characteristics emphasized in the original Featherstone, Roessler, and Barry (2006) framework. Extending the baseline model to incorporate farm type provided modest improvement in predictive performance, with permanent planting loans exhibiting higher estimated default risk than crop loans. Incorporating delinquency history produces a substantially greater increase in discrimination, with AUC increasing to 0.971. However, because the delinquency history was constructed retrospectively using the observed loan period, these findings do not establish the same predictive performance for loans evaluated prospectively.

The TTC analysis extended the baseline framework by retaining annual loan-year observations and incorporating national and state-level macroeconomic conditions. Across 83,052 loan-year observations, borrower repayment capacity, leverage, and loan amount maintained relationships with default that were generally consistent with those identified in the PIT analysis. Total Debt Coverage Ratio was negatively associated with default, while Debt-to-Asset Ratio and Log Loan Amount exhibited positive and statistically significant relationships with default in the annual TTC specifications. Original Loan to Value Ratio was not statistically significant. The consistency of these relationships across the two modeling approaches reinforces the importance of borrower financial condition in agricultural credit risk assessment.

The inclusion of macroeconomic variables provided additional information about annual agricultural loan default, although the estimated relationships differed across economic measures. In the full contemporaneous TTC specification, annual Real GDP Growth and State Net Cash Farm Income were negatively and statistically significantly associated with default in the estimated specifications, while CPI Inflation was not statistically significant. These findings suggest that stronger national economic growth and state-level agricultural income conditions are associated with lower default risk after controlling for borrower financial characteristics. However, incorporating macroeconomic variables produced only modest improvements in model discrimination, with AUC increasing from 0.673 in the baseline TTC model to 0.677 in the full macroeconomic specification. The results therefore suggest that broader economic conditions provide supplementary information without substantially improving the ability of the models to distinguish between default and nondefault observations.

The TTC robustness and lagged macroeconomic analyses provided further insight into the stability of these relationships. Under the alternative default definition of delinquency code 3

or greater, borrower repayment capacity, leverage, and loan amount maintained consistent directions and statistical significance. The macroeconomic relationships were somewhat more sensitive to the default threshold, particularly for Real GDP Growth, which was no longer statistically significant in the full specification under the broader definition. The lagged analysis indicated that State NCFI maintained a negative and statistically significant association with current year default when measured using the preceding year's economic conditions. In contrast, lagged Real GDP Growth was not statistically significant. These findings suggest that state-level agricultural income provides relatively consistent information about default risk across alternative model specifications, while the estimated relationships with national economic conditions depend partly on the timing of the measures and the definition of default.

The credit risk classification analysis further demonstrated the ability of the baseline PIT model to distinguish among loans with different estimated levels of default risk. Applying the historical probability thresholds developed by Featherstone, Roessler, and Barry (2006) placed a substantial share of the Farmer Mac portfolio in the higher risk categories. Loans assigned to these categories generally exhibited lower repayment capacity, greater leverage, and larger loan amounts. Comparisons between predicted and observed default rates also showed relatively close agreement in the largest risk classes, providing evidence of in-sample risk differentiation and calibration. However, because the historical classification thresholds were developed using different data and default horizons, the resulting classes should be interpreted as relative risk categories within the Farmer Mac portfolio rather than as directly equivalent to external credit ratings.

Several limitations should be considered when interpreting these findings. The PIT analysis summarizes each loan's observed history into a single observation, and the resulting

default probabilities do not correspond to a standardized prediction horizon. Additionally, the retrospective construction of the delinquency history indicator limits the interpretation of its predictive performance. Although the TTC analysis retains the time dimension of the data through annual loan-year observations, repeated observations of individual loans and shared exposure to macroeconomic conditions may introduce dependence that is not fully reflected in conventional logistic regression standard errors. The estimated macroeconomic relationships should therefore be interpreted cautiously. Furthermore, the reported classification performance measures are based on the estimation samples rather than independent validation data, limiting conclusions about how the models would perform when applied to new loans or future periods.

Future research could extend this analysis by evaluating default probabilities over standardized prediction horizons and incorporating additional measures of agricultural economic conditions. Constructing delinquency history indicators using only information available before the prediction period would allow repayment behavior to be evaluated as a prospective predictor of default. Additional research could also examine alternative approaches for accounting for repeated loan observations and common macroeconomic shocks, strengthening statistical inference within the TTC framework. Evaluating model performance on separate loans or later time periods would provide further evidence of predictive reliability. Recalibrating risk classification thresholds to reflect contemporary agricultural loan portfolios and consistent default horizons could improve the practical usefulness of probability-based credit risk classifications. Finally, outcomes other than probability of default, such as demand for new credit (i.e., Ifft, Kuhns, and Patrick, 2018), are extensions that may be of interest to both lenders and policymakers.

Overall, the findings indicate that borrower financial condition remains a central component of agricultural loan default risk assessment. Repayment capacity, leverage, and loan amount exhibit consistent relationships with default across the PIT and TTC approaches, while repayment behavior and macroeconomic conditions contribute additional information in different ways. The results reinforce the importance of borrower-level financial characteristics identified in earlier agricultural credit risk research and demonstrate that state-level agricultural income conditions provide supplementary information about annual default risk. By applying an established agricultural credit risk framework to a more recent national loan portfolio, this study provides updated evidence on the factors associated with agricultural real estate loan default and the usefulness and limitations of probability-based risk classification.

References

"About Farmer Mac | Our Mission and Impact." n.d. Accessed November 1, 2026. https://www.farmermac.com/about.

Bandyopadhyay, Arindam. 2007. "Credit Risk Models for Managing Bank's Agricultural Loan Portfolio." MPRA Paper. National Institute of Bank Management, Pune, India, October 12. https://mpra.ub.uni-muenchen.de/5358/.

Brewer, Brady E., Christine A. Wilson, Allen M. Featherstone, J. Michael Harris, Ken Erickson, and Charles Hallahan. 2012. "Measuring the Financial Health of U.S. Production Agriculture." *Journal of ASFMRA*, 178–93.

Briggeman, Brian C., Michael A. Gunderson, and Brent A. Gloy. 2009. "The Financial Health of Agricultural Lenders." *American Journal of Agricultural Economics* 91 (5): 1406–13.

Castro, Carlos, and Karen Garcia. 2014. "Default Risk in Agricultural Lending, the Effects of Commodity Price Volatility and Climate." *Agricultural Finance Review* 74 (4): 501–21. https://doi.org/10.1108/AFR-10-2013-0036.

"Consumer Price Index for All Urban Consumers: All Items in U.S. City Average." 2026. October 14. https://fred.stlouisfed.org/series/CPIAUCSL.

Durguner, Seda, and Ani L. Katchova. 2007. *Credit Scoring Models in Illinois by Farm Type: Hog, Dairy, Beef and Grain*. Selected Paper 173058. https://doi.org/10.22004/ag.econ.9356.

"Farm Income and Wealth Statistics - Net Cash Income." n.d. Accessed November 1, 2026. https://data.ers.usda.gov/reports.aspx?ID=4024.

Featherstone, Allen M., Laura M. Roessler, and Peter J. Barry. 2006. "Determining the Probability of Default and Risk-Rating Class for Loans in the Seventh Farm Credit District Portfolio." *Review of Agricultural Economics* 28 (1): 4–23.

Featherstone, Allen M., Christine A. Wilson, Terry L. Kastens, and John D. Jones. 2007. "Factors Affecting the Agricultural Loan Decision-making Process." *Agricultural Finance Review* 67 (1): 13–33. https://doi.org/10.1108/00214660780001195.

Featherstone, Allen M., Christine A. Wilson, and Lance M. Zollinger. 2017. "Factors Affecting Risk-Rating Migration." *Agricultural Finance Review* 77 (1): 181–95. https://doi.org/10.1108/AFR-05-2016-0044.

Ferch, Kaci E. 2023. *Determining the Probability of Default for Agrifinancial's Loan Portfolio*.

Foglia, A., S. Iannotti, and P. Marullo Reedtz. 2001. "The Definition of the Grading Scales in Banks' Internal Rating Systems." *Economic Notes* 30 (3): 421–56. https://doi.org/10.1111/1468-0300.00066.

Ifft, Jennifer, Ryan Kuhns, and Kevin Patrick. 2018. "Can Machine Learning Improve Prediction – An Application with Farm Survey Data." *International Food and Agribusiness Management Review* 21 (8): 1083–1098. https://doi.org/10.22434/IFAMR2017.0098

Jacobson, Tor, and Kasper Roszbach. 2003. "Bank Lending Policy, Credit Scoring and Value-at-Risk." *Journal of Banking & Finance* 27 (4): 615–33. https://doi.org/10.1016/S0378-4266(01)00254-0.

Johnson, Andrew M., Michael D. Boehlje, and Michael A. Gunderson. 2017. "Agricultural Credit Risk and the Macroeconomy: Determinants of Farm Credit Mid-America PD Migrations." *Agricultural Finance Review* 77 (1): 164–80. https://doi.org/10.1108/AFR-06-2016-0057.

Jouault, Amelie, and Allen M. Featherstone. 2011. *Determining the Probability of Default of Agricultural Loans in a French Bank*.

Katchova, Ani L., and Peter J. Barry. 2005. "Credit Risk Models and Agricultural Lending." *American Journal of Agricultural Economics* 87 (1): 194–205.

Key, Nigel. 2022. "Credit Constraints and the Survival and Growth of Beginning Farms." *Agricultural Finance Review* 82 (3): 448–63. https://doi.org/10.1108/AFR-04-2021-0050.

Lacy, K., Fuller, K. B., Raszap Skorbiansky, S., & Lim, K. (2026). America's farms and ranches at a glance: 2025 edition (Report No. EIB-299). U.S. Department of Agriculture, Economic Research Service. https://doi.org/10.32747/2026.9460427.ers

Limsombunc, Visit, Christopher Gan, and Minsoo Lee. 2005. "An Analysis of Credit Scoring for Agricultural Loans in Thailand." *American Journal of Applied Sciences* 2 (8): 1198–205. https://doi.org/10.3844/ajassp.2005.1198.1205.

Parcell, Joe, Jennifer Ifft, and Alice Roach. 2025. "Probability of Kansas Loan Default." *RaFF Policy Brief* 2025-8(3). Rural & Farm Finance Policy Analysis Center, University of Missouri. https://raff.missouri.edu/wp-content/uploads/2025/08/2025-8-3-RaFF-Policy-Brief.pdf

"Real Gross Domestic Product." 2026. October 29. https://fred.stlouisfed.org/series/gdpc1.

Sabasi, Darlington, C. Richard Shumway, and Lyudmyla Kompaniyets. 2021. "Analysis of Credit Access, U.S. Agricultural Productivity, and Residual Returns to Resources." *Journal of Agricultural and Applied Economics* 53 (3): 389–415. https://doi.org/10.1017/aae.2021.17.

Sabato, Gabriele. 2010. "Credit Risk Scoring Models." SSRN Scholarly Paper No. 1546347. Social Science Research Network, February 2. https://doi.org/10.2139/ssrn.1546347.

Wolf, C. A., and J. Karszes. 2023. "Financial Risk and Resiliency on US Dairy Farms: Measures, Thresholds, and Management Implications." *Journal of Dairy Science* 106 (5): 3301–11. https://doi.org/10.3168/jds.2022-22711.