

Modeling forward-looking state-level farm financial stress using bank loan delinquency data

by

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Abstract

During the past 20 years, and since the restructuring of the USDA Economic Research Service's farm economy division, minimal work has been done to track farm financial measures at the state or regional levels. Instead, farm financial research has tended to focus on national-level measures. Policymakers often react to stakeholder testimony about concerns of waning farm income when creating ad-hoc agricultural economic relief policies. Having a more robust leading indicator of state-level farm financial well-being can improve policies being implemented and lead to better timing of ad-hoc economic recovery payments. This study aggregates a commonly used banking stress-test measure of loan delinquency rate as a proxy for the counter-party farm financial well-being.

Loan delinquency rates in this study were estimated by using Federal Reserve commercial bank and Farm Credit call data to compute a combined delinquency rate for each state to measure farm financial stress. Variables for the models included crop revenues, livestock revenues, lagged government payment revenues, total expenses, and lagged delinquency rates. Historical state-level explanatory variable data is from the Economic Research Service (ERS) and then 10-year forward-looking estimates are from Rural & Farm Finance Policy Analysis Center (RaFF).

In comparing three alternative models of individual state models, pooled panel state models, and state delinquency rates with national explanatory variable data, the pooled panel state models provided results that are consistent with economic theory and returned a high statistical fit. The lagged delinquency rates had the largest impact on loan delinquency rates, indicating that hard, or good, times of financial stress will linger in the following years. While direct government payments also showed to be a useful tool in supporting producers financially.

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Chapter 1 - Introduction

1.1 Motivation:

Agricultural policy has the dual goal of enhancing production for food security while stabilizing farms' financial positions. Research has argued that such government intervention is necessary. Calomiris et al. (1986) suggested an economic case exists for government intervention in agriculture due to deviations from perfect markets. The government also has political, social and national defense rationales for implementing meaningful agricultural policies. Hughes, Richardson and Rister (1985) highlighted three issues — two policy-related — that contributed to farm difficulties during the 1980s farm debt crisis: macroeconomic policies, farm policies and individual management decisions.

Perhaps as the 1980s farm crisis demonstrates, policymakers often struggle to measure a policy decision's true impact on an industry or sector's financial health. For farms, multiple stressors pose financial risks. For example, some operations generate seasonal income flows, particularly if they have limited diversification or only a single enterprise. Regional disruptions, such as droughts, severe weather events and disease outbreaks, and macroeconomic challenges such as trade wars and recessions can trigger changes in supply, demand or prices and cause farm financial strain. In the case of agriculture, however, any farm-sector financial trouble or policies designed to mitigate it not only affect the farms themselves but also service and input providers, rural economies and end-users. With respect to farm lenders, Featherstone, Roessler, and Barry (2006) emphasize that "Credit risk is the primary risk facing financial institutions." This underscores the importance of addressing farm financial challenges to ensure the resilience of the agricultural finance system.

The U.S. farm sector’s diversity means “one-size-fits-all” agricultural policies intended to control some of the financial risks to farms and benefit farm businesses could spark some unintended short- and long-term negative consequences when applied uniformly throughout the country. Policy analysis allows for measuring the full true effect of farm safety net and other government support programs — including their financial implications — before policies are approved and enacted.

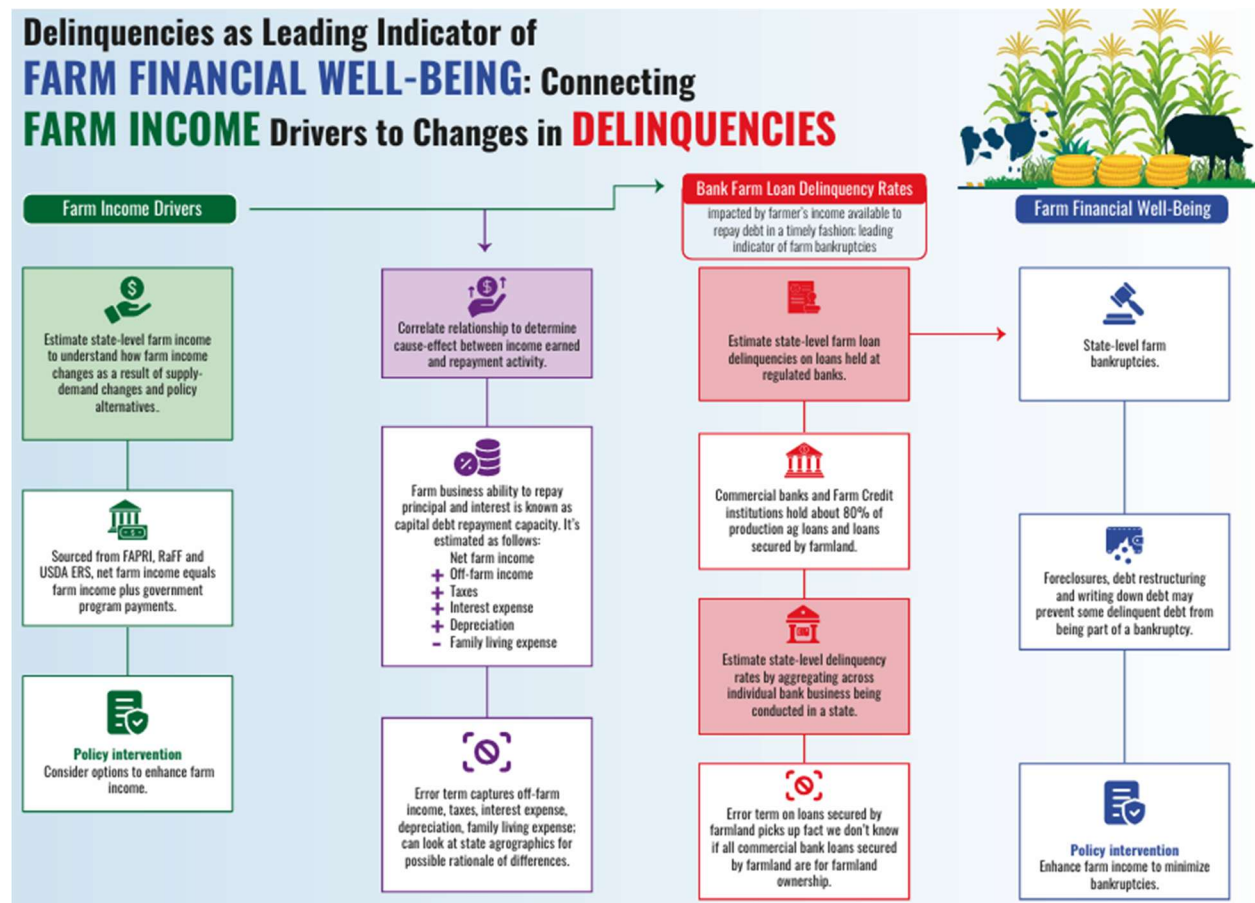
Economic models that forecast the relative impact of proposed policy change are not new. Both the USDA and the Food & Agricultural Policy Research Institute (FAPRI) at the University of Missouri produce baseline projections that assess what policy changes could mean for the agricultural economy. The existing policy analysis work includes at best approximating policy effects on farm financial well-being, particularly at the state or regional levels. Therefore, the current research has the following objective:

The current research analyzes the effectiveness of the correlation between an estimated state-level proxy variable for farm financial well-being (i.e., farm loan delinquency rates) with state-level farm revenue and expense estimates within a seven-state region. Finding a high level of fit between past loan delinquency rate levels and farm revenue and expenses yields correlation relationships that can be tied to forecasts of farm revenue and expense to estimate a forward-looking baseline of state-level agricultural financial stress.

Given a lack of access to raw farm financial data, this study uses farm loan delinquencies that are ninety days past due plus nonaccrual loans as a proxy for farm financial stress because delinquencies are an indicator of farmers’ ability to meet debt obligations. It specifically draws on farm loan delinquency data Farm Credit association banks and commercial banks, which collectively extend close to 80% of agricultural debt (USDA ERS). Commercial banks and Farm Credit association banks are regulated and submit quarterly financial data on the performance of agricultural loans and loans secured by farmland. Delinquency rates reflect, by loan

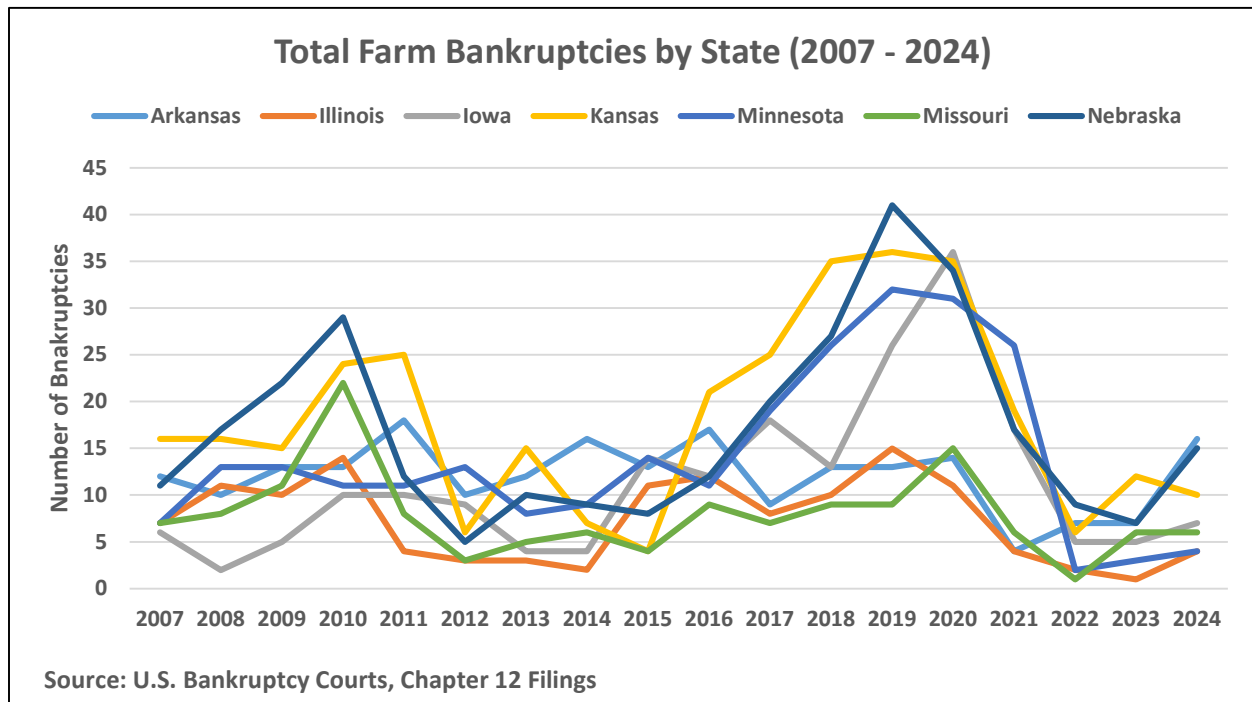
classification, total delinquent loan volumes as a share of total loan volume. **Figure 1.1** helps illustrate what drives farm incomes and how farm financial well-being is assessed in the present research.

Figure 1.1: Delinquencies as leading indicator of farm financial well-being



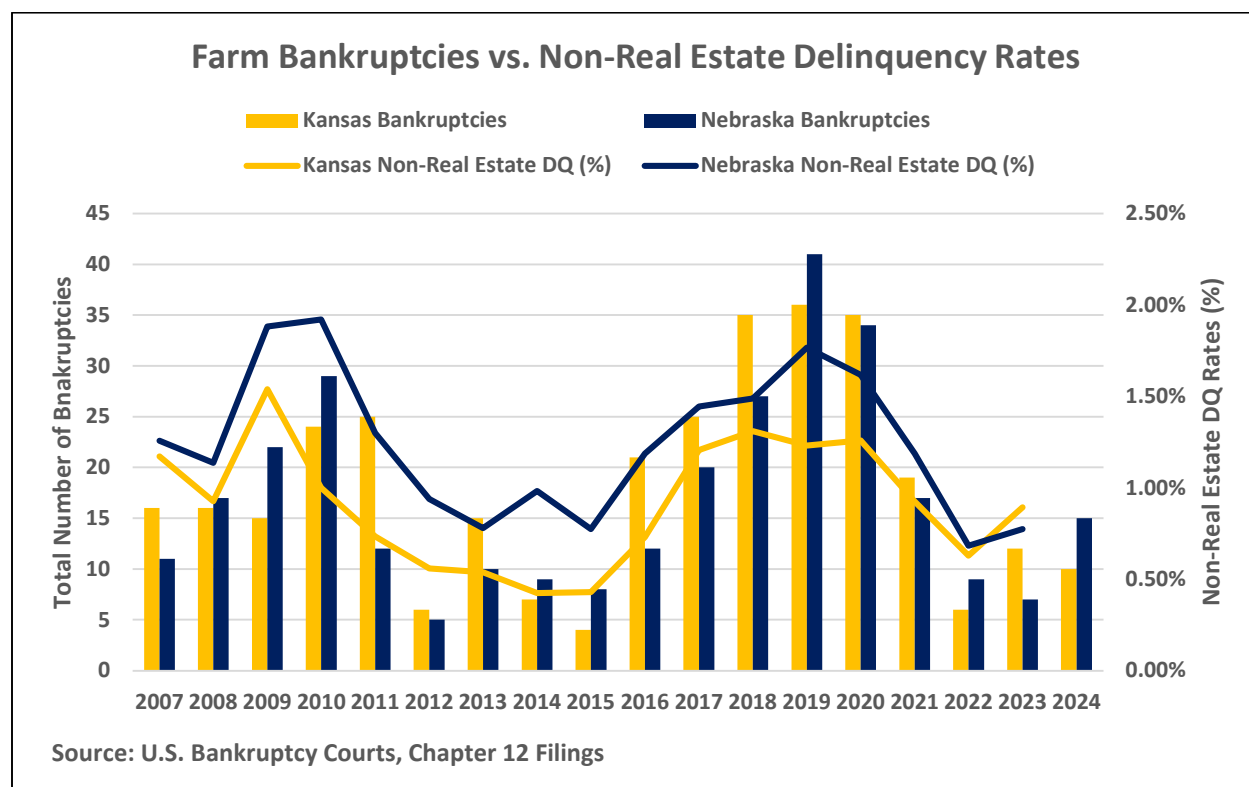
Ultimately, farm loan delinquencies can reshape U.S. agriculture if they lead to farm bankruptcies and closures. **Figure 1.2** shows the trend in total farm bankruptcies — those in chapter 12 bankruptcy — for the seven states included in this research.

Figure 1.2: Total Farm Bankruptcies by State



When comparing spikes in delinquency rates to total farm bankruptcies in the seven-state area, there is a visual correlation between the non-real estate delinquency rates and total bankruptcies. For Kansas and Nebraska only, **Figure 1.3** compares the total number of farm bankruptcies with estimated non-real estate delinquency rates aggregated for both commercial and Farm Credit association banks in each state. It shows a high correlation between the total number of bankruptcies and loan delinquency rates.

Figure 1.3: Kansas and Nebraska Farm Bankruptcies vs. Non-Real Estate Delinquency Rates



Dinterman et al. (2018) used chapter 12 bankruptcy datasets to model variables that impact bankruptcy rates from the filings. They found the most significant determinants impacting farm bankruptcies was the lagged value of agricultural land having a negative relationship. This was the only significant agricultural variable in their model, but macroeconomic factors such as interest and unemployment rates were strong predictors of farm bankruptcies as well.

Estimating the relationship between past delinquency levels and farm revenue and expense variables can be used in conjunction with farm revenue and expense forecasts to generate forward-looking estimates of state-level agricultural financial stress (i.e., loan delinquencies). This framework creates an opportunity to analyze how policy changes or

recommendations not only impact farm income but also farm financial well-being and ultimately economic stress in rural economies.

For example, consider the trade war that unfolded from 2018 to 2020. Large ad hoc government payments disseminated through the Market Facilitation Program infused cash into U.S. farms feeling the trade policy's negative effects and helped to improve farm business financial health. What could have happened if the Market Facilitation Program hadn't been created? How would these effects be absorbed differently throughout the country? Could changes to the program have yielded longer term farm financial solvency and repayment capacity? For future policy analysis, answers to questions like these are possible with the results of the present research.

1.2 Agricultural Lending:

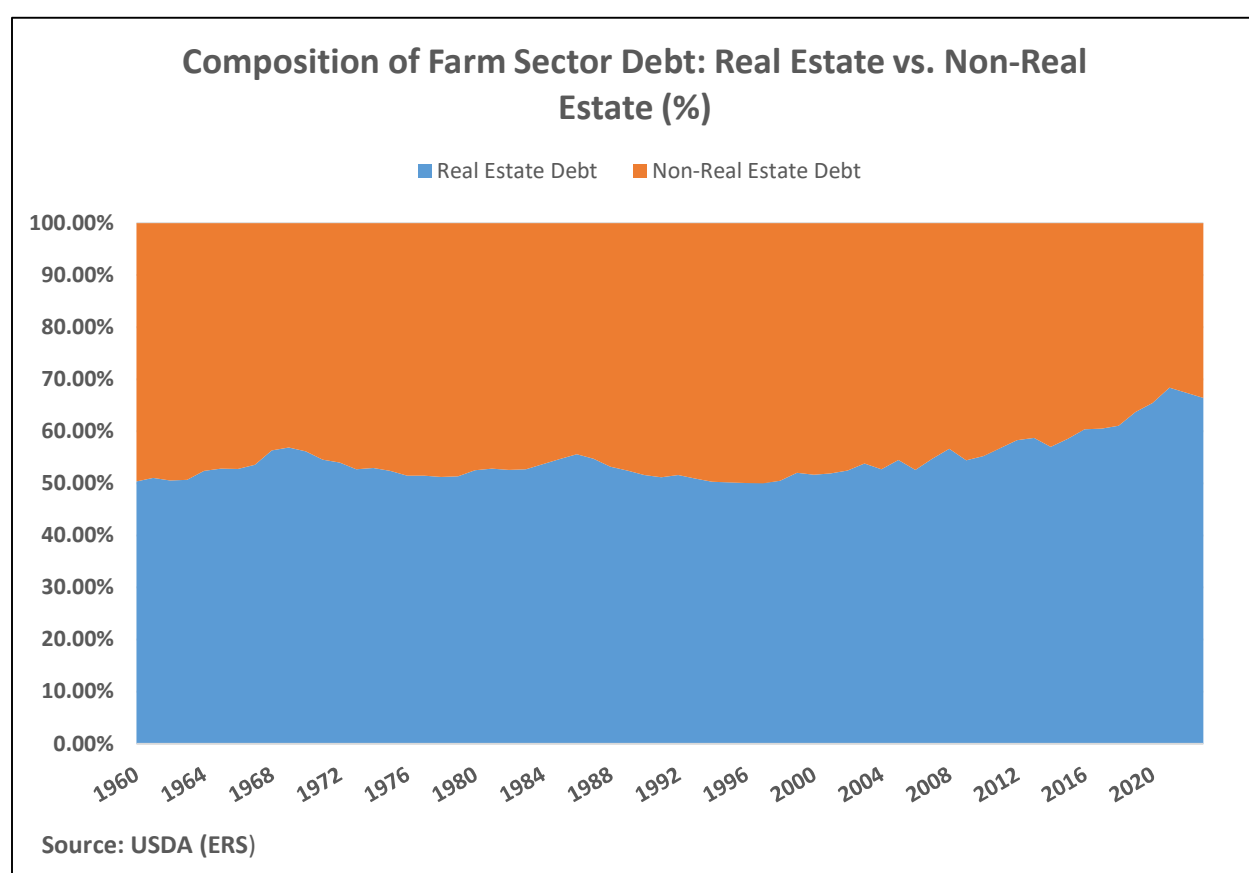
Agricultural producers traditionally have had access to several financing options, including commercial banks, agricultural credit associations part of the Farm Credit System (FCS), the USDA Farm Service Agency (FSA) and private lenders. The FCS and commercial banks collectively hold the largest share of reported agricultural loan volume. Commercial banks tend to cater to more diverse farm sizes and operations and often address liquidity through a wider range of credit products (Brewer, Bergtold, Featherstone, & Wilson, 2019). In contrast, the USDA FSA often supports higher-risk borrowers, such as those who are less financially secure or beginning farmers and ranchers. A previous study found that the most financially secure Kansas producers with lower debt levels and higher assets accessed credit from FCS lenders (Brewer, Bergtold, Featherstone, & Wilson, 2019).

The farm sector carries two types of debt: real estate and non-real estate (USDA ERS).

Figure 1.4 shows the distribution of agricultural debt between categories remained relatively

balanced from the 1960s to roughly 2010, when non-real estate debt began to account for a larger share of total reported debt. Separately, in aggregate nationally the farm balance sheet tends to indicate solid solvency. For example, in 2015, the debt-to-asset (DTA) ratio for the U.S. farm sector stood at approximately 12.39%. The DTA ratio then peaked in 2020 at 14.10% before declining to 12.93% in 2023 (USDA ERS). However, aggregated farm financial data is known to mask both regional and farm type differences (Key, Burns, & Lyons, 2019).

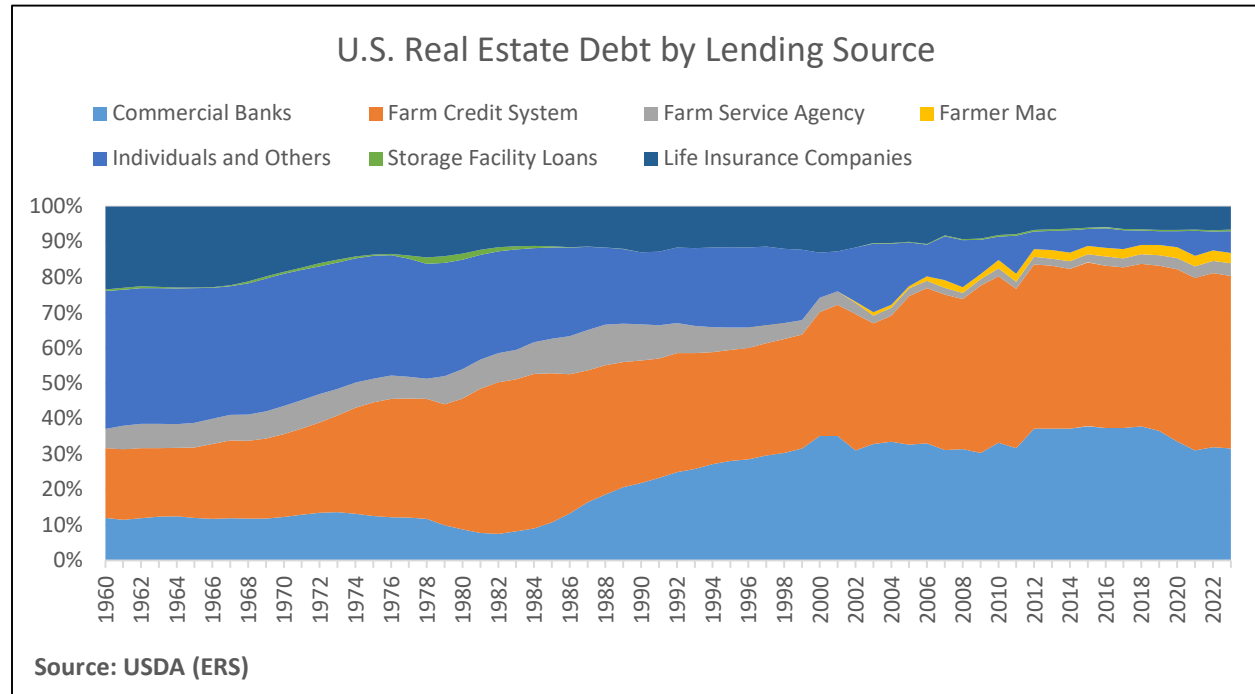
Figure 1.4: Composition of Estimated Farm Sector Debt: Real Estate vs. Non-Real Estate



In terms of the types of lenders financing farm-sector debt types, **Figure 1.5** depicts U.S. Real Estate Debt as a percentage of total Farm Sector funding. In recent years, most real estate

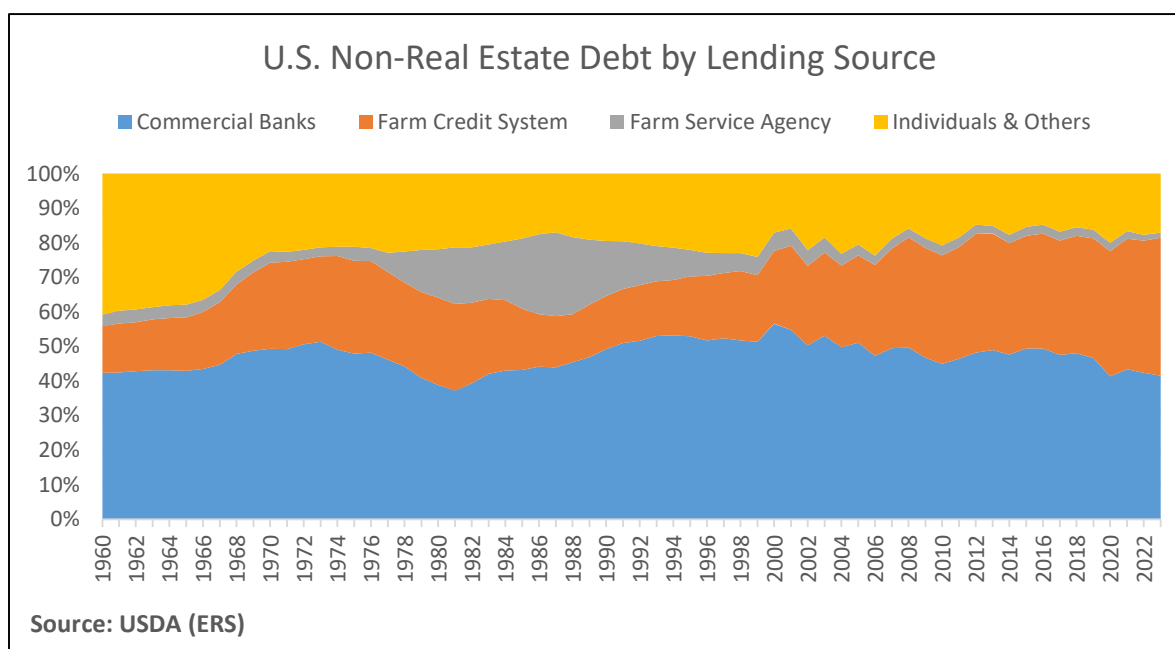
financing has been extended by two institutions: FCS and Commercial Banks, which today make up over 70% of the total market share for real estate debt.

Figure 1.5: U.S. Real Estate Debt by Lending Source



The **Non-Real Estate Debt** category, as illustrated in **Figure 1.6**, reflects a similar trend, with Farm Credit Services (FCS) and commercial banks dominating over 80% of the market share, while lending from individuals and other sources has remained relatively stagnant. In 2021, Farm Credit, commercial banks, and the USDA FSA collectively accounted for 83.22 cents of every outstanding dollar in loans (Subedi & Giri, 2024).

Figure 1.6: U.S. Non-Real Estate Debt by Lending Source



The main theme over time for both categories has been an increase in the market share of FCS and commercial banks, while the FSA has seen diminishing percentages of loans sourced from them. Which is no surprise as FCS and commercial banks are easily accessible to producers and provide competitive rates while the FSA acts more of as a lender of first opportunity.

1.3 Economic Value:

State-level modeling of delinquency rates offers numerous benefits, extending beyond localized insights contributing to a broader national understanding of policy decisions' impacts. Such models not only enhance the comprehension of policy effects but also help sustain the infrastructure of farm lending to help monitor financial stress to producers that then impacts lending institutions, a critical component of maintaining a healthy agricultural economy. These models provide vital insights for economists and policymakers, offering a predictive framework

to understand how policies may reshape the agricultural landscape and impact producers' financial viability.

For instance, policy shifts that lead to increased delinquencies could force policy makers to then raise the capital requirements for financial institutions, ensuring stability in the lending sector and preventing a financial collapse, which would create widespread changes in the agricultural lending industry. This is particularly important as the U.S. continues to lose farms — due to reasons such as smaller farms closing or operations filing for bankruptcy. According to Keller and Kassel (2025), the number of farms dropped by 8% from 2017 to 2024.

This study reports on modeling delinquency rates as a proxy for state-level farm financial stress across seven states: Arkansas, Illinois, Iowa, Kansas, Minnesota, Missouri and Nebraska. Three models are analyzed: 1) correlations between state delinquency levels and state farm income and expenses levels forming a panel regression approach; 2) individual state-level models of state delinquency levels and state farm income and expense levels; and 3) models expressed as state-level delinquency rates as a function of national income and expense levels.

Delinquency rates are computed using commercial bank call report data from the Federal Deposit Insurance Corporation and Farm Credit association call data from the Farm Credit Administration. Income and expense data are provided by the Rural and Farm Finance Policy Analysis Center (RaFF) at the University of Missouri, which pulls historical income and expense estimates from USDA and applies baseline projections for future years up to 2032.

By modeling state-level and national delinquencies, this study aims to provide a comprehensive framework for assessing how income and expense dynamics influence loan delinquency rates across agricultural producers. These models serve as baseline estimates to evaluate the financial vulnerabilities of farms under different economic and policy conditions.

Understanding whether a national model offers broader insights or whether state-specific models provide more precise projections is crucial for policymakers and financial institutions seeking to mitigate farm financial stress. Findings from this research will contribute to a more informed approach in designing policies that enhance farm financial resilience and sustainability.

Chapter 2 - Literature Review

Elevated agricultural loan delinquency rates carry significant financial implications. Prior research has extensively examined credit conditions within the financial industry, farm use of debt financing and farmer sentiment as indicators of farm financial health. These studies influenced the approach taken in this research and ultimately guided the decision to model state-level farm incomes to analyze farm loan delinquency rates.

To measure the aggregate health of the farm sector, Key, Burns and Lyons (2019) highlighted which farms were under the most financial stress in the 2010s. They measured farm financial factors, such as net farm income, farm debt and interest, farm real estate and debt-to-asset ratios, that give key insights into the overall health of the sector and analyzed farm-level factors of liquidity, solvency and financial stress. The study used USDA Agricultural Resource Management Survey (ARMS) results to provide farm-level data for the analysis.

In that same study, stress tests were done with data by farm size to determine which farms would be most affected by a decrease in net farm income. By estimating multiple decreases of 10% and then 20% in gross cash farm income, they determined large farms would see the biggest increase in extreme financial stress when farm income falls. They found that if gross revenue decreased by 20%, the share of large farms in financial stress would increase to 6.7% — much higher than the estimated 3.7% of large farms in financial stress in 2017.

Featherstone, Roessler and Barry (2006) analyzed expected loss rates for lenders by decomposing expected loss into three key components: probability of default, loss given default and exposure at default. Their study focused on the Seventh Farm Credit District Portfolio, utilizing a dataset of 157,853 loans to model the probability of default based on factors such as repayment capacity, owner equity and working capital. During the time of the study, the Seventh

Farm Credit District was made up of 11 states: Arkansas, Illinois, Indiana, Kentucky, Michigan, Minnesota, Missouri, North Dakota, Ohio, Tennessee and Wisconsin. The study applied a binary logit regression approach to estimate default probabilities and mapped them onto Standard & Poor's (S&P) risk-rating classifications. The findings suggest that most risk-rating systems incorporate quantitative and qualitative elements, but financial institutions often more greatly emphasize repayment capacity and solvency rather than profitability and financial efficiency when assessing credit risk. The study underscores the importance of more granular risk-rating systems and highlights how financial institutions can refine their credit risk models to improve capital management and regulatory compliance.

Although default risk modeling provides valuable insights into creditworthiness, understanding borrower characteristics is also essential in assessing farm financial stability. Brewer et al. (2019) found farmers' choice in lender is determined by multiple factors: DTA ratios, liquidity capabilities and the ability to spread credit risk. The typical farm lenders studied in this study, Farm Credit and commercial banks, have different portfolio characteristics, and nontraditional lending is starting to see more interest from producers. Farm Credit customers tend to have larger farms with full-time operators, commercial banks cater to more diverse operations and serve a younger portfolio, and nontraditional lenders provide vendor financing linked to specific agricultural segments (Brewer, Bergtold, Featherstone, & Wilson, 2019). Nontraditional lenders are categorized as "the primary contact for business with a producer is not lending". This same study expressed concerns about the credit risk associated with nontraditional lending. Although vendor financing and alternative credit sources may provide a safety net, they also raise broader questions about the overall creditworthiness of the agricultural sector.

Diving deeper into lender portfolios, Fiechter et al. (2024) studied farmer sentiment and the impact on USDA FSA direct loan applications. The USDA FSA is a lender of “first opportunity” and helps socially disadvantaged groups access credit (Dodson & Ahrendsen, 2017). The findings from this study are twofold: 1) a positive relationship between farmer sentiment and farm ownership loan applications and 2) a negative relationship between farmer sentiment and direct operating loan applications.

The Federal Reserve Bank of Kansas City conducts a quarterly ag credit survey to provide indicators of financial performance of the 10th district. Briggeman and Zakrzewicz (2009) evaluated whether the survey was a viable option for predicting national credit conditions. The study stemmed from 2009 net farm incomes dropping by nearly 40% (Briggeman & Zakrzewicz, 2009). Tighter income levels greatly impacted producers’ ability to repay loans. The study stated that delinquent non-real estate farm loans are preliminary signs of stress in agricultural credit markets because they are used to meet short-term capital needs. The research found forecasts by agricultural lenders reliably predicted farm financial stress.

Katchova and Barry (2005) employed a credit value-at-risk (VaR) framework using Illinois Farm Business Farm Management (FBFM) data to assess credit risk in agricultural lending. Their study examined historical defaults and losses, calculated both expected and unexpected losses and conducted sensitivity analyses to evaluate how changes in risk exposure impact farm debt. By applying two different models, they estimated probabilities of default, loss given default and exposure at default for borrowers. Their findings emphasized the importance of risk granularity, showing that farm financial risk varies significantly across borrower classes.

Results from Katchova and Barry reinforced the idea for this study that the risk of default is granular and varies across borrower classes and that analyzing even further across a seven-

state model could better depict credit risk for various regions. Each state has a different makeup of agricultural producers who may cause lenders to have a diverse portfolio of borrowers.

This study coincides with an agricultural downturn. Crop prices and revenues have decreased, but livestock receipts have seen an uptick due to heightening cattle prices. The Federal Reserve Bank of Kansas City conducts quarterly ag credit surveys, and in the first quarter of 2024, the biggest downturn in credit conditions was in states that rely heavily on crop revenues, particularly in areas that saw poor growing conditions relative to the rest of the corn and soybean belts. Strong cattle prices supported profits for cow-calf producers (Kauffman & Kreitman, 2024). The article also had comments from bankers about the impact higher interest rates may have on producers experiencing poor liquidity conditions.

These macroeconomic trends further emphasize the need for regionalized credit risk modeling. By analyzing delinquency rates across multiple states, this study aims to provide a more nuanced understanding of how state-specific economic conditions influence farm financial stability and loan repayment behavior.

There are two studies that utilized the same delinquency rate estimates as the present research. The first is Roach, Parcell, Ifft, and Fiechter (2024). They used vector autoregressive modeling to test how well two factors — banker sentiment about repayment captured in Federal Reserve Bank surveys and corn futures price — serve as leading indicators of farm loan delinquencies. Using this modeling approach, they modeled nonaccrual loan status across Illinois, Iowa, Kansas, Missouri, Nebraska, and Texas. The study found the Dallas sentiment index was a better predictor than the corn futures price of state-level farm loan delinquency rates.

The second study from Parcell, Ifft, Roach, Warren, and Francis (2024) measured the directional change of nonaccrual status on loans in commercial banks and Farm Credit

Administration data at the national, regional and state levels. The thesis behind this study is that a change in sentiment or market price has a direct impact on the farm economy's health. What was found is that the commercial bank national data is a better predictor when comparing the commercial bank and Farm Credit data. The study also found a national model better predicts changes in farm economic health than the regional or state level values. Interestingly, corn futures were found to be as good as or a better predictor than the sentiment predictors.

Chapter 3 - Methodology

To analyze state-level loan delinquency rates, a basic panel ordinary least squares (OLS) regression was employed. As outlined in the **Model Variable Descriptions** section, non-real estate delinquencies from commercial banks and Farm Credit associations were combined to compute a single non-real estate delinquency rate. The same methodology was applied to calculate the real estate delinquency rate. This approach allowed for developing two separate models — one for non-real estate loans and one for real estate loans — covering a seven-state region: Arkansas, Illinois, Iowa, Kansas, Minnesota, Missouri and Nebraska.

3.1 State Delinquency Models

State-level delinquency models offer a foundation for predictive policy analysis. They incorporate FAPRI and RaFF future data, which serve as baseline projections at the national and state levels, respectively, and include USDA historical values. Given the evolving landscape of federal government programs, such as those provided by the American Relief Act, 2025, these models can be instrumental in assessing the potential impact of policy changes on agricultural loan delinquency rates. This predictive framework enables scenario analysis, so policymakers and financial institutions can better anticipate credit risk fluctuations under different economic and policy scenarios.

For this study, the only changes in the state-level models are the dependent variable and the lagged delinquency rates. The first model is the **Non-Real Estate Delinquency Model**, and the second state-level model is the **Real Estate Delinquency Model**. These models will incorporate their respective delinquency rates while following the framework below. The two **National Models** that incorporate national income and expense variables are highlighted in the fifth and sixth equations:

Seven-State Panel Models

$$(1) \text{ Non-RealEstateDQ}_{st} = B_1 \text{CropRevenues}_{st} + B_2 \text{LivestockRevenues}_{st} +$$

$$B_3 \text{TotalExpenses}_{st} + B_4 \text{DirectGovPayments}_{st-1} + B_5 \text{Non-RealEstateDQ}_{st-1} +$$

$$\sum^7 \delta_s D_s + \mathcal{E}_{st}$$

$$(2) \text{ RealEstateDQ}_{st} = B_1 \text{CropRevenues}_{st} + B_2 \text{LivestockRevenues}_{st} +$$

$$B_3 \text{TotalExpenses}_{st} + B_4 \text{DirectGovPayments}_{st-1} + B_5 \text{RealEstateDQ}_{st-1} + \sum^7 \delta_s D_s + \mathcal{E}_{st}$$

Seven-State Individual State Models

$$(3) \text{ Non-RealEstateDQ}_{st} = B_0 + B_1 \text{CropRevenues}_{st} + B_2 \text{LivestockRevenues}_{st} +$$

$$B_3 \text{TotalExpenses}_{st} + B_4 \text{DirectGovPayments}_{st-1} + B_5 \text{Non-RealEstateDQ}_{st-1} + \mathcal{E}_{st}$$

$$(4) \text{ RealEstateDQ}_{st} = B_0 + B_1 \text{CropRevenues}_{st} + B_2 \text{LivestockRevenues}_{st} +$$

$$B_3 \text{TotalExpenses}_{st} + B_4 \text{DirectGovPayments}_{st-1} + B_5 \text{RealEstateDQ}_{st-1} + \mathcal{E}_{st}$$

National Income & Expenses Models

$$(5) \text{ Non-RealEstateDQ}_{st} = B_0 + B_1 \text{NationalCropRevenues}_t +$$

$$B_2 \text{NationalLivestockRevenues}_t + B_3 \text{NationalTotalExpense}_t + B_4 \text{DirectGovPayments}_{t-1}$$

$$+ B_5 \text{Non-RealEstateDQ}_{st-1} + \mathcal{E}_{st}$$

$$(6) \text{ RealEstateDQ}_{st} = B_0 + B_1 \text{NationalCropRevenues}_t + B_2 \text{NationalLivestockRevenues}_t +$$

$$B_3 \text{NationalTotalExpense}_t + B_4 \text{DirectGovPayments}_{t-1} + B_5 \text{RealEstateDQ}_{st-1} + \mathcal{E}_{st}$$

The subscript st in the state-level equations represent the panel data structure, where s denotes the state, and t denotes the annual time period. This structure allows the model to account for cross-sectional differences across states and variations over time in loan delinquency rates. The national models follow the same structure, and only the loan delinquency rates change

between states as the national data are used as independent variables except for the lagged delinquency rate.

While it may seem intuitive to just use net farm income values instead of crop revenues, livestock revenues, government payments and expenses as variables, the hypothesis was that the individual variable characteristics would capture the state or regional differences better than just using net farm incomes. For example, Kansas and Nebraska rely more heavily on livestock revenues than Illinois does. Models using net farm income variables less government payments and using the lagged delinquency rates were created to check this hypothesis. When compared to the results of the more distinct variables, it was determined the net farm income results did not capture state level differences as well and did not have as high of a statistical fit.

The first two equations are for the seven-state region's pooled panel regression. With data only being available from 2005 to 2023, this allows for 18 observations per state. Running a seven-state panel model allows for testing whether a more robust model encompassing all observations as a single region impacts forecasts relative to models for individual states or a national model. The third and fourth equations follow the same methodology, but because they are individual state regressions, no dummy variables are included. In the pooled panel regression, there are twelve total variables as there are seven binary variables for each state involved in the study to create a fixed effects model within each state.

Equations five and six indicate the national models. Total income and expenses are the same for each state to determine the best predictor of loan delinquencies. The goal is to determine which best predicts loan delinquencies: a seven-state region model, individual state-level models or national models.

By incorporating lagged delinquency rates, the equations account for the dynamic nature of financial stress. In other words, problems don't usually dissipate quickly between business cycles, and for an industry with seasonal revenue, times of stress persist into the next year. Additionally, including state dummy variables ($\sum^7 \delta_s D_s$) controls for state-specific fixed effects, capturing unobserved characteristics that may influence delinquency rates beyond the explanatory variables. This should isolate the impact of crop revenues, livestock revenues and government payments on loan delinquencies while accounting for underlying state-level differences in economic conditions.

The expected results are that higher crop revenues, higher livestock revenues and lagged government payments will show lower delinquency rates and produce negative coefficients in both models. In contrast, total expenses and lagged delinquency rates are expected to have positive coefficients, implying that higher expenses and elevated past delinquency rates contribute to an increase in future delinquencies. The lagged delinquency rate coefficient is particularly important as it provides insights into the persistence of financial stress in agricultural lending. Understanding this persistence can help lenders and economists anticipate future credit risk trends. Table 3.1 notes expected coefficient results.

Table 3.1: Expected Coefficient Results

Expected Signs of Coefficients		
Variable	Non-Real Estate	Real Estate
Crop Revenues	-	-
Livestock Revenues	-	-
Total Expenses	+	+
Government Payment Revenues Lagged	-	-
Lagged Delinquency Rate	+	+

Variable Description:

Estimated Non-Real Estate Loan Delinquency Rates: An overall loan delinquency rate for non-real estate loan portfolios was calculated by combining the delinquency volumes from commercial banks and Farm Credit institutions of delinquencies that were ninety days or more past due and plus nonaccrual loans. This total was then divided by the combined total loan volumes to determine the overall non-real estate loan delinquency rate for each state. The combined total loan volumes are total loan volumes from the Farm Credit call data and the commercial bank call data. Non-real estate loans consist of operating notes, livestock loans, equipment loans and more, which are expected to reflect the financial health of agricultural operations in the short term.

Estimated Real Estate Loan Delinquency Rates: Like with the non-real estate delinquency rate calculation, total real estate delinquencies from commercial banks and Farm Credit institutions were combined to calculate an overall delinquency rate for real estate loans that are ninety days past due plus nonaccrual loans, which are loans secured by farmland. This rate was derived by dividing the combined total delinquencies by the total loan volume for farmland-secured loans. Although real estate loans are generally intended for farmland purchases or improvements, the precise proportion of these loans exclusively used for farmland is uncertain. This is because some short-term debt can be converted into long-term debt as part of an operator's strategic capital allocation to balance immediate operational needs with long-term financial planning. All income and expense values at both the state level and national level are provided by FAPRI and USDA.

Lagged Delinquency Rates: For both non-real estate and real estate delinquency models, lagged delinquency rates were included as a variable in their respective models. This decision was based

on the understanding that financial hardships often persist from year to year and improve minimally unless influenced by external factors such as government intervention or other significant events. Consequently, lagged delinquency rates were anticipated to be statistically significant for each state and model, reflecting the enduring nature of farm financial difficulties.

Crop Revenues: Derived from historical USDA crop receipts revenue data, these values exclusively reflect revenues generated from cropping enterprises and are reported annually. This variable was selected because agricultural production varies significantly across the seven states. For instance, Illinois relies heavily on row crop production for its agricultural revenue, but Kansas has a more diversified mix of crop and cattle production.

Livestock Revenues: Historical data for total annual livestock revenues by state originate from USDA, and RaFF makes future projections. Like with the crop revenues variable, livestock revenue was selected as a variable to account for differences in each state's farms.

Total Expenses: This variable represents total agricultural expenses reported annually for each state. While initially developing the seven-state model, various breakdowns of expense were tested, but only a few had statistical significance. After consolidating these into a single total expense value, the model's statistical significance improved and yielded more robust and reliable results. This streamlined approach allowed for a clearer understanding of the relationship between total agricultural expenses and the other variables in the model.

Lagged Government Payments: Government payments contribute significantly to agricultural revenues, particularly during periods of financial stress. The decision to lag these payments is based on the logic that payments received in one year tend to have a greater impact on financial conditions in the following year. This is because producers often use government payments to cover expenses incurred at the beginning of the next production cycle. This reasoning was

validated in the seven-state model; direct government payments were not statistically significant until they were lagged. Again, government payment values come from the USDA, and state-by-state projections are estimated by RaFF.

3.2 Establishing Baseline for Forward-Looking Delinquency Rates

Creating forward-looking baseline models of farm loan delinquencies can help policymakers understand how changes in policy impact farm financial well-being. Policy changes shift not only short-term government outlays, commodity revenues and expenses but also influence intermediate-term operational changes. For example, producers adjust cropping decisions, purchase decisions and marketing decisions if they anticipate changes in government outlays. This study uses September 2024 FAPRI national baseline estimates and RaFF October 2024 state-level baseline estimates to arrive at a state-level baseline for revenue, expenses, production and income. The state-level baseline assumes average weather and current policy continuing for the next 10 years. Using coefficients from the delinquency rate models, the 10-year state-level baseline financial estimates can be multiplied with the coefficients to produce baseline loan delinquency rates by state for 10 years in the future (i.e., 2024 to 2032 in the present case). The forward-looking estimated delinquency rates serve as a baseline. Tweaking the assumptions allows economists to analyze how policy shocks change the delinquency rate from the baseline. Subsequently, policymakers benefit from better understanding the substantiation, and persistency, of a policy change on the farm financial well-being of among their states' constituents.

For the current research, only the baseline-estimated delinquency rates between 2024 and 2032 are presented. At the present time, FAPRI-RaFF had not released an updated baseline that reflected payments (i.e., economic aid, disaster assistance) authorized by the American Relief

Act, 2025, which allocated nearly \$30 billion to farmers. If the updated baseline RaFF models were available, then the models presented in Chapter 5 could be updated and used to compare differences between fall 2024 baseline delinquency rates (pre-policy) and estimated spring 2025 baseline delinquency rates (post-policy). This assessment would detail how the policy changed short- and intermediate- term financial well-being for each of the seven states.

Chapter 4 - Data

This study utilized four main data sources to build the seven-state model at both the state level and national level. Key data on state farm income and expenses were sourced from USDA ERS and projections of revenue and expenses from FAPRI and RaFF at the University of Missouri. The other two data sources were the commercial bank and Farm Credit call reports.

4.1 Farm Income Data from USDA ERS

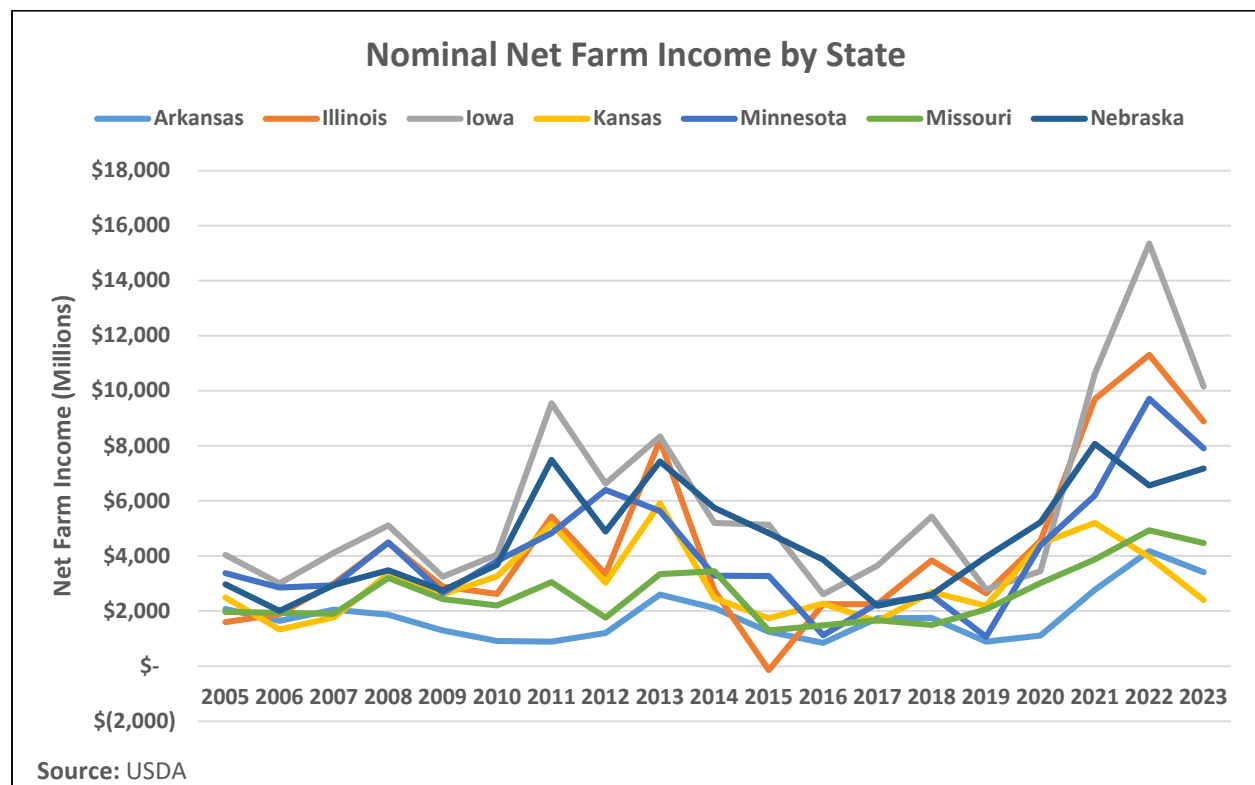
The USDA estimates net farm income using data retrieved from the National Agricultural Statistics Service, ARMS and USDA Farm Service Agency's Commodity Credit Corporation (CCC) (USDA ERS). Total receipts by production type (e.g., crops, livestock) are determined. The USDA then takes all calculated farm expenses and subtracts that number from gross farm income to calculate net farm income.

All USDA farm income and expense estimates were in nominal values, so using FAPRI deflator values, the data were converted into real values for analysis. Choosing real values allows us to use the forecasted values in the future with the model results to predict what policy changes may do to loan delinquency rates. Without converting nominal values to real values, we would be unable to compare variables from the past, today and future to accurately depict dollar values that hold the same economic impact. The USDA uses real returns in its 10-year livestock and poultry baseline models that forecast carcass weights, sows farrowing, chicks hatched and other variables (Maples, Brorsen, Hahn, MacLachlan, & Chalise, 2022).

By state, **Figure 4.1** shows the recent net farm income trend for the seven-state region on a nominal basis. Net farm incomes posted low levels during part of the Great Recession, drought in 2012, financial stress period from 2015 to 2019 and trade war in 2019. Higher net farm income was recorded in 2011, 2013, 2014 and during the commodity run-up in 2022 and 2023.

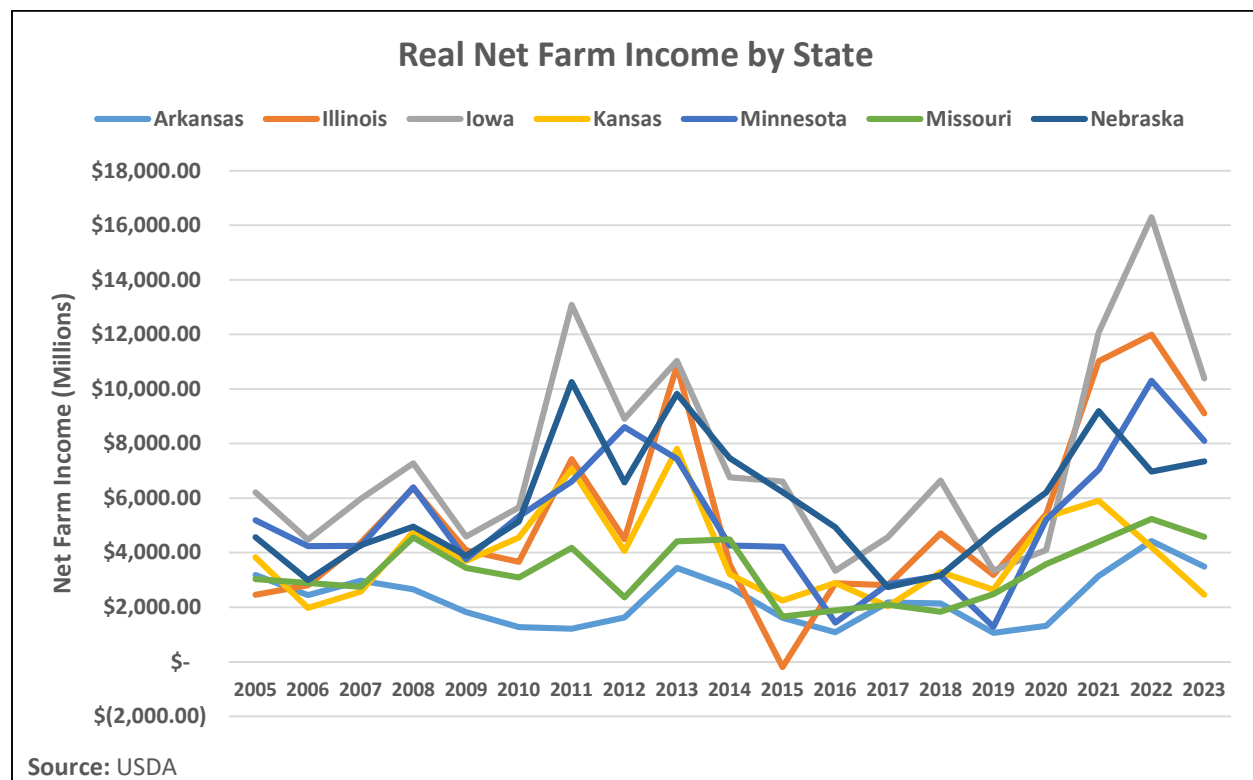
Net farm income affects financial stress risk within agriculture. Times of financial stress impact economic activity far beyond the producer, and because of this, policymakers often intervene and offer support in the form of ad hoc payments. During the period shown in **Figures 4.1 and 4.2**, significant government intervention arrived during stressful times to help stimulate the agricultural economy. The modeling produced for this study intends to serve as an additional framework that tests how policy actions, including ad hoc payments, would affect farm credit conditions and stress at the state level. Low nominal net farm income values during the Great Recession led spikes in agricultural delinquency rates shown in **Figures 4.3 and 4.4**.

Figure 4.1: Nominal Net Farm Income by State



Real net farm income values, which were produced by adjusting the nominal values reported by USDA, are seen in **Figure 4.2**.

Figure 4.2: Real Net Farm Income by State



4.2 Commercial Bank & Farm Credit Data:

Modeling reflects loan delinquency rates from commercial banks and Farm Credit associations for loans that are more than ninety days past due and includes nonaccrual loans. Delinquency rates for commercial banks were calculated using the federal regulated Consolidated Report of Condition and Income (Call Reports), which all federally regulated insured banks are required to file on a quarterly basis. To determine non-real estate (or non-farmland secured) delinquency rates, the annual volume of delinquent production agricultural loans by state was divided by the total annual production agricultural loan volume. Similarly, for real estate loans secured by farmland, the total delinquent loan volume was divided by the total loan volume secured by farmland.

Total delinquent loan volumes and total loan volumes were estimated for both commercial banks and Farm Credit. For both Farm Credit and commercial banks, the call data

are institution-specific and illustrate a particular institution's portfolio size and financial performance, not actual loan volumes or loan performance for a particular geography. The summary of deposits dataset provided by the Federal Deposit Insurance Corporation (FDIC) lists the branch locations affiliated with the banks required to report quarterly call data. The branch deposit file allowed for accounting for every county where a bank operates. A portion of a bank's loan portfolio would be distributed to each county where a bank had an open facility. Because this analysis isn't concerned about market share, we did not weight presence in a county by the number of branch banks in a county affiliated with a single headquarter (HQ) bank.

To estimate loan volume by county for commercial banks, the 2017 farm interest expense reported in the U.S. Census of Agriculture was used. For each bank reporting call data, the sum of farm interest expenses across all counties the bank serves were found. Multiplying the share of interest expense incurred in one county within a bank's footprint by a bank's loan volume, which is reported in quarterly call data available from the FDIC's Research Information System (RIS), would estimate a bank's loan volume in the given county. The county-level estimates were aggregated to the state level to estimate a bank's loan volume by state.

Farm Credit associations submit quarterly data like commercial banks do, and the Farm Credit Administration (FCA) reports this information publicly. FCA publishes call data specific to each institution, not the geographic area covered by the institution, so each agricultural credit association must be associated with the counties where the particular institution had the authority to lend in 2023. This was done using the FCS Institution Directory, which provides a map and territory description with county names listed for each institution in the system.

To approximate the extent to which loans are distributed across institutions' territories, loan volumes were distributed according to the share of interest expense reported by county

within an institution's territory. The interest expense data originated from the 2017 U.S. Census of Agriculture data. This method was applied to estimate loan volumes, and the health of those loans, carried by county for FCS institutions that existed in 2023.

A simple allocation method accounted for counties over chartered by Farm Credit institutions (i.e., a county is served by more than one agricultural credit association). For example, a county served by two associations was assigned to both associations. This scenario affects a small number of counties, which are generally very rural and large by area. If a county is overchartered, then all expenses in the county are assigned to each association listed for the county. This could lead to overallocation in these counties and underallocation in other counties served by an association, but the total impact of overallocation in a county was negligible.

Like other segments of the financial sector, the FCS has experienced merger and acquisition activity over time. To account for this, in our data series of historical farm loan performance, predecessor institutions that became part of the institutions existing in 2023 were inventoried. Call data for these predecessor institutions were aggregated to picture what an institution today would have looked like in the past if all its predecessor institutions had been joined together historically.

Total loan volumes approximated for counties then were summed into state estimates. The aggregated data was used as the state-level quarterly financial data for this study. **Table 4.1** lists delinquency rates by institution and state.

Table 4.1: Loan Delinquency Rates by State, Institution and Loan Type

Farm Credit Delinquency Rates - Non-Real Estate						Farm Credit Bank Delinquency Rates - Real Estate					
State	Unit	Average	S.D.	Minimum	Maximum	State	Unit	Average	S.D.	Minimum	Maximum
Arkansas	%	0.70%	0.29%	0.29%	1.34%	Arkansas	%	0.65%	0.23%	0.29%	0.98%
Illinois	%	0.89%	0.56%	0.29%	2.49%	Illinois	%	0.64%	0.45%	0.23%	1.63%
Iowa	%	0.87%	0.55%	0.15%	2.39%	Iowa	%	0.38%	0.17%	0.15%	0.61%
Kansas	%	0.70%	0.37%	0.15%	1.88%	Kansas	%	0.63%	0.32%	0.28%	1.31%
Minnesota	%	0.87%	0.47%	0.36%	2.19%	Minnesota	%	0.83%	0.61%	0.31%	2.11%
Missouri	%	0.68%	1.15%	0.06%	4.48%	Missouri	%	0.51%	0.57%	0.06%	2.11%
Nebraska	%	0.87%	0.55%	0.15%	2.39%	Nebraska	%	0.38%	0.17%	0.15%	0.61%

Commercial Bank Delinquency Rates - Non-Real Estate						Commercial Bank Delinquency Rates - Real Estate					
State	Unit	Average	S.D.	Minimum	Maximum	State	Unit	Average	S.D.	Minimum	Maximum
Arkansas	%	1.22%	0.38%	0.66%	1.85%	Arkansas	%	2.30%	0.66%	1.25%	3.91%
Illinois	%	0.90%	0.36%	0.49%	1.74%	Illinois	%	1.31%	0.42%	0.67%	2.34%
Iowa	%	1.04%	0.44%	0.42%	2.11%	Iowa	%	1.07%	0.37%	0.62%	1.92%
Kansas	%	1.05%	0.40%	0.50%	1.68%	Kansas	%	1.64%	0.65%	0.87%	2.93%
Minnesota	%	1.18%	0.46%	0.66%	2.27%	Minnesota	%	1.83%	0.71%	0.87%	3.27%
Missouri	%	0.73%	0.20%	0.43%	1.06%	Missouri	%	1.47%	0.46%	0.71%	2.42%
Nebraska	%	1.34%	0.41%	0.71%	2.00%	Nebraska	%	1.38%	0.37%	0.81%	2.21%

As anticipated, state-level trends in loan delinquency rates closely align with state net farm incomes. For the model, total loan delinquency values and total loan volumes from commercial banks and Farm Credit data were combined to calculate an annual overall estimated weighted-average loan delinquency rate for each state. Combined data are termed as “banking sector” loan data in this paper. For the banking sector, **Figures 4.3** and **4.4** show delinquency rates for non-real estate and real estate loans over time.

Figure 4.3: Non-Real Estate Loan Delinquency Rates by State

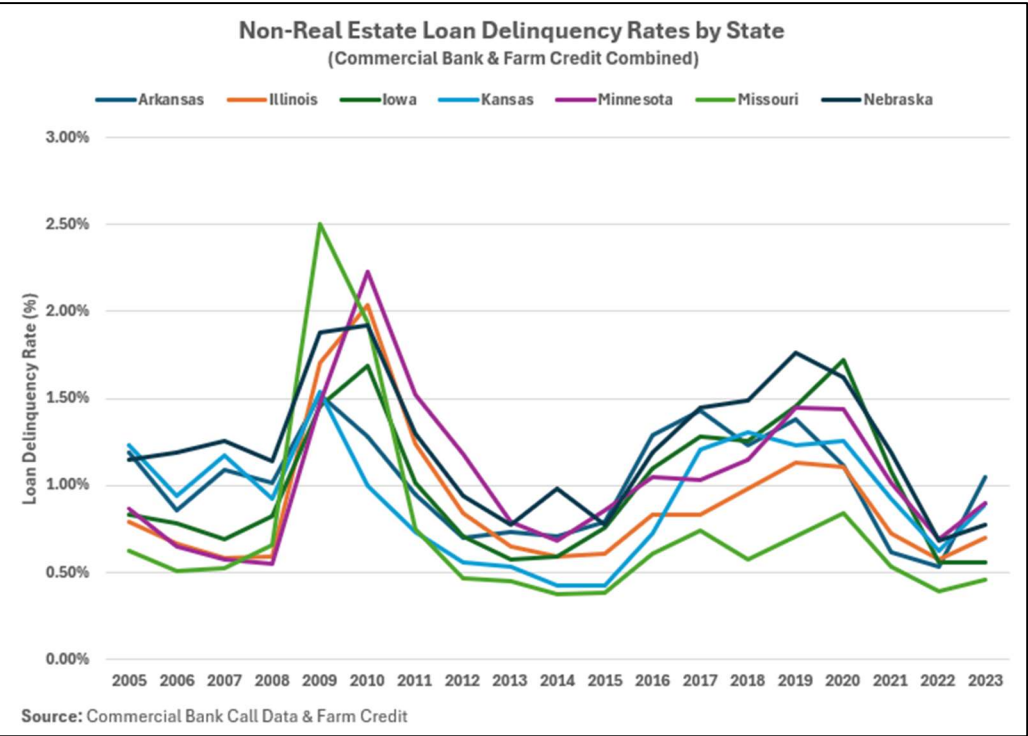
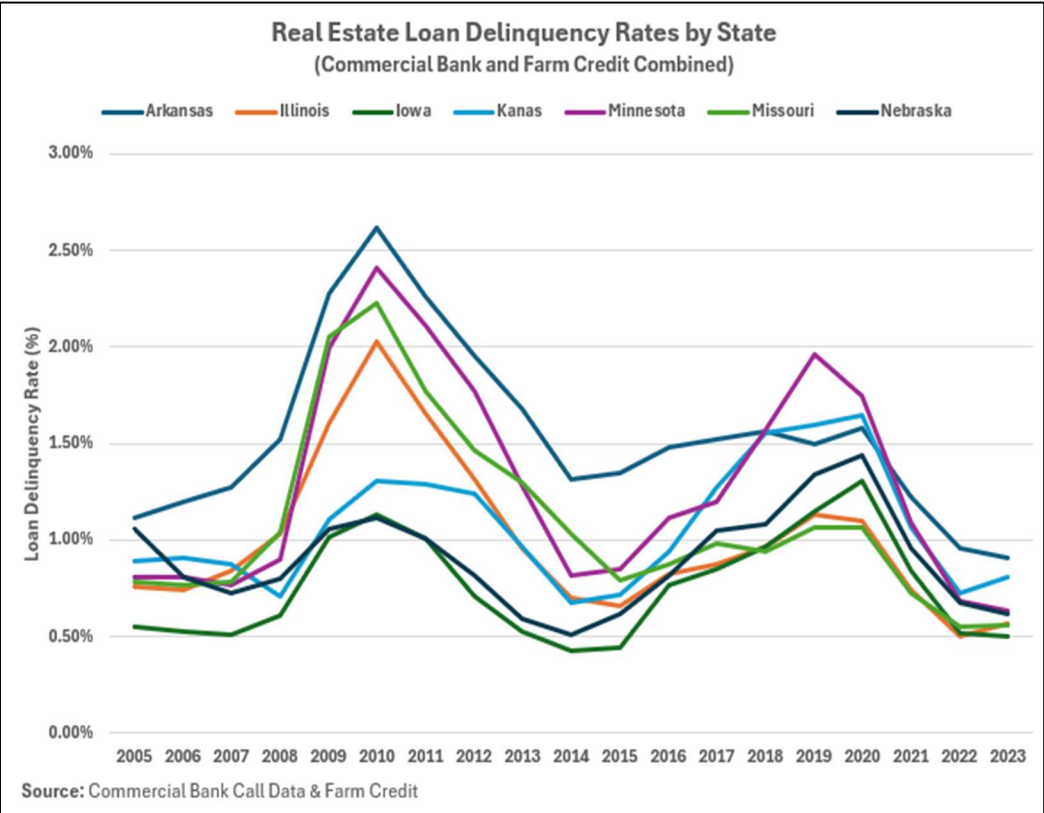


Figure 4.4: Real Estate Loan Delinquency Rates by State



Correlation coefficients between real net farm income and the combined banking sector delinquency rates for non-real estate and real estate loans are seen in **Table 4.2**. The correlations are bivariate for presentation purposes. Finding correlation using a multivariate analysis should yield more robust correlates that reflect covariance between factors expected to affect changes in delinquency rates. The correlates between state-level income are on the top horizontal axis, and either non-real estate or real estate for each state is listed on the left vertical axis.

Table 4.2: Loan Delinquency Rates and Net Farm Income Correlation Coefficients

Loan Type	Arkansas	Illinois	Iowa	Kansas	Minnesota	Missouri	Nebraska
Non-Real Estate	-0.515	-0.193	-0.527	-0.205	-0.179	-0.054	-0.460
Real Estate Secured	-0.643	-0.146	-0.307	0.156	-0.183	-0.037	-0.312

The correlation coefficients between loan delinquency rates for non-real estate and real estate loans and net farm income by state provide valuable insights. Overall, the results reveal a negative correlation across most states, indicating that higher net farm income is generally associated with lower loan delinquency rates. This relationship is particularly strong in states such as Arkansas, Iowa and Nebraska, where the coefficients for both loan types are significantly negative (e.g., -0.515 for non-real estate loans in Arkansas and -0.643 for real estate-secured loans). However, the strength of the correlation varies by state. For example, negative correlations in Missouri and Illinois were weaker (e.g., -0.054 and -0.037 for Missouri real estate-secured loans). This suggests factors beyond net farm income may play a larger role in influencing delinquency rates in these states. Interestingly, Kansas displays a positive correlation for real estate-secured loans (0.1568), standing out as an exception and questioning potential underlying data issues or exceptions to the underlying assumption. The positive correlation could

be due to a variety of reasons. It is important to understand that aggregate farm income reflects a lot of moving pieces: crop revenues, livestock revenues, government payments and expenses.

The correlation coefficients also show that real estate-secured loans tend to have slightly stronger negative correlations compared to non-real estate loans, indicating that fluctuations in net farm income may have a more pronounced impact on the health of loans tied to farmland, which are often larger and directly linked to farm profitability. States such as Arkansas and Iowa with stronger negative correlations highlight the direct influence of farm financial stability on loan repayment behavior. These findings emphasize the importance of economic conditions and policies that support net farm income as they could significantly affect reducing loan delinquencies. The variability in correlation strength across states also underscores the need to consider regional differences when modeling financial stress and policy impacts on agriculture.

4.3 USDA, FAPRI & RaFF Data:

FAPRI's mission is to provide reliable, research-based analysis to support agricultural policy decision-making. To achieve this, FAPRI develops baseline projections for U.S. agricultural markets that offer insights into the trajectory of current policies over a defined future period. RaFF has used the FAPRI baseline projection estimations as the backbone for creating state-level baselines for several U.S. states; see **Figures 4.5** and **4.6**. Projections extend through 2032 and serve as a foundation for economists to introduce policy “shocks,” which are scenarios that allow for evaluating the long-term outcomes resulting from policy changes. This foundation is crucial to this study as it facilitates projecting future delinquency rates at the state level.

To help researchers and policymakers better understand the data available, FAPRI produced a paper on how it conducts policy analysis (Meyers, Westhoff, Fabiosa, & Hayes, 2010). The paper states all models are dynamic, partial equilibrium, multi-product, non-spatial

econometric models. This allows the models to generate accurate baselines for supply and demand tables that incorporate the most up-to-date USDA World Agricultural Supply and Demand Estimates data. In this study, data comes from the corresponding state farm income and expenses datasets compiled by RaFF to include their baseline forecasts.

Note, the FAPRI baseline projections assume current national policies, normal growing conditions and trend rates of technological growth (Meyers, Westhoff, Fabiosa, & Hayes, 2010). RaFF projections do the same. Therefore, loan delinquency rate projections in this paper assume continuation of current policies and do not represent policy shocks, catastrophic weather events or other technological change. That said, this study's results will give coefficients to help determine what would happen to delinquencies as farm income and expenses change. **Appendix A** presents RaFF-published state-level baseline projection variables by state through 2032.

Figure 4.5: Nominal Net Farm Income Projections by State

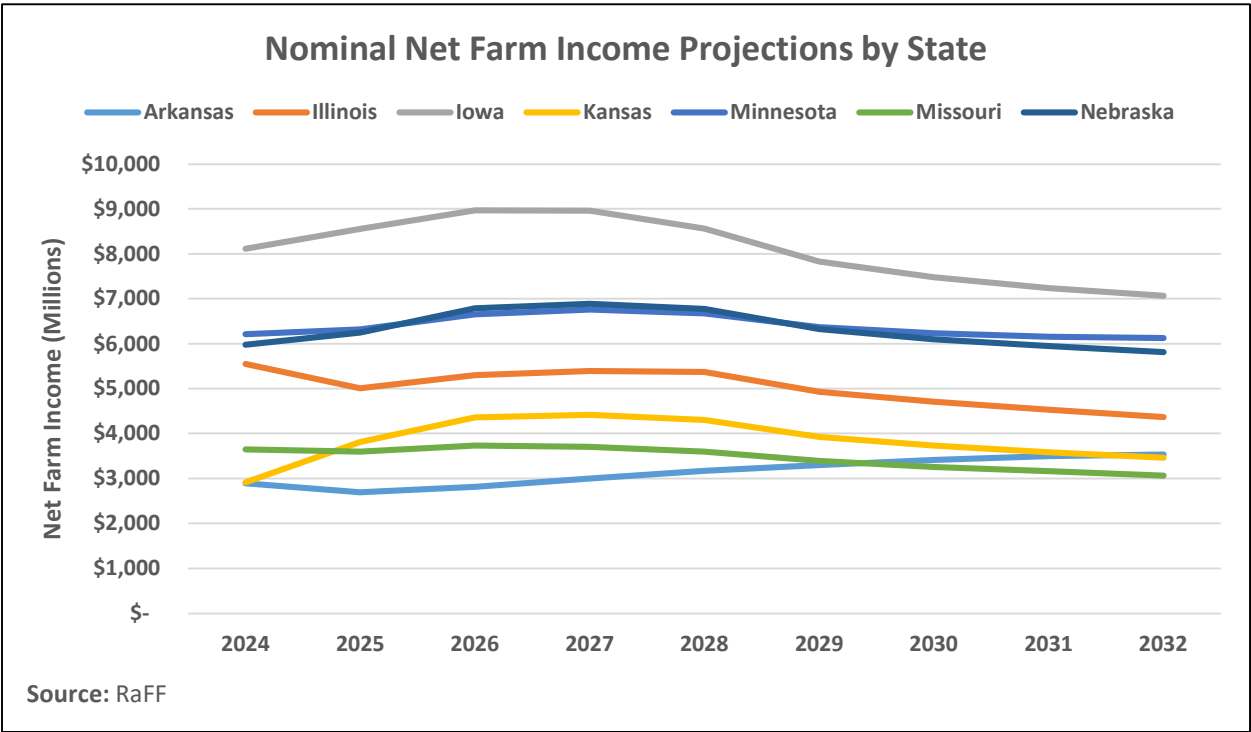
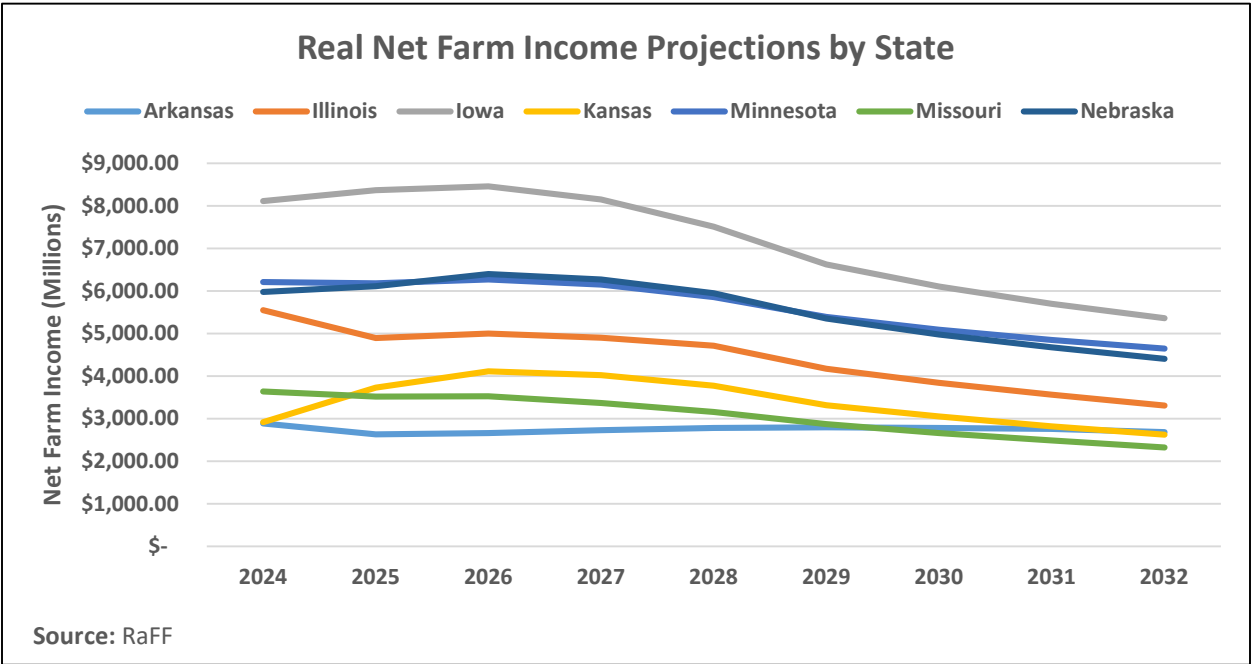


Figure 4.6: Real Net Farm Income Projections by State



As seen in **Figure 4.5** and **4.6**, net farm income is expected to plateau in 2026 and then decrease to roughly 2024 levels or even lower for each state based on the current policy and market prices. Changes to basic supply and demand factors, policies or other external factors could influence net farm income; however, these values provide a framework for researchers to shock and measure how policy changes would affect farm financial conditions.

Three sets of models were created: seven-state panel model, individual state model and state delinquency national income model. The seven-state panel model utilized panel regression to produce coefficients for each variable to encompass a total regional result. The individual state model was run for each state using state-level income and expense data. The national model used state-level delinquencies but national income and expenses. The intent was to identify the best predictor of farm loan delinquencies. **Table 4.3** summarizes each model's data sources.

Table 4.3: Model Description

Variable	7-State Panel Model	Individual State Model	National Model
Delinquency Rate	State Level	State Level	State Level
Income/Expense Variables	State Level	State Level	National Level

Models had five independent variables for each of the non-real estate and real estate loan model types: Crop Revenues, Livestock Revenues, Total Expenses, Lagged Non-Real Estate Delinquency Rates, Lagged Real Estate Delinquency Rates and Lagged Direct Government Payments. They had two dependent variables: Combined Non-Real Estate Loan Delinquency Rates and Combined Real Estate Loan Delinquency Rates. In total each model had five independent variables for each non-real estate and real estate model, not including binary variables that are used in the panel model, and all dollar values were converted to real terms with

the baseline year being 2024. The national model used the same delinquency rates as each respective state and national income and expense variables.

4.4 Variable Summary Statistics:

Table 4.4 provides the following summary statistics for all variables from 2005 to 2023: units, average, standard deviation, minimum and maximum.

Table 4.4: Summary Statistics of Data Used to Estimate 7-State Loan Delinquency Rate Models

Estimated Non-Real Estate Delinquencies		Unit	Average	S.D.	Minimum	Maximum
	Arkansas	%	1.03%	0.29%	0.54%	1.52%
	Illinois	%	0.90%	0.40%	0.58%	2.04%
	Iowa	%	1.00%	0.38%	0.56%	1.72%
	Kansas	%	0.93%	0.33%	0.42%	1.54%
	Minnesota	%	1.06%	0.42%	0.55%	2.23%
	Missouri	%	0.74%	0.55%	0.38%	2.50%
	Nebraska	%	1.23%	0.38%	0.68%	1.92%
Estimated Real Estate Delinquencies						
	Arkansas	%	1.54%	0.45%	0.91%	2.62%
	Illinois	%	1.00%	0.40%	0.50%	2.02%
	Iowa	%	0.76%	0.27%	0.42%	1.31%
	Kansas	%	1.07%	0.31%	0.68%	1.65%
	Minnesota	%	1.29%	0.56%	0.63%	2.41%
	Missouri	%	1.09%	0.47%	0.55%	2.23%
	Nebraska	%	0.90%	0.26%	0.51%	1.44%
Real Crop Revenues (2024 Base Year)						
	Arkansas	\$/Million	\$4,926	\$855	\$3,487	\$6,667
	Illinois	\$/Million	\$18,591	\$4,053	\$10,770	\$25,853
	Iowa	\$/Million	\$18,619	\$4,373	\$10,186	\$26,892
	Kansas	\$/Million	\$8,236	\$1,592	\$5,017	\$11,144
	Minnesota	\$/Million	\$12,939	\$3,125	\$6,838	\$18,481
	Missouri	\$/Million	\$6,654	\$1,342	\$3,875	\$9,295
	Nebraska	\$/Million	\$12,482	\$3,066	\$6,076	\$17,369
	National	\$/Million	\$250,412	\$34,517	\$178,162	\$311,329
Real Livestock Revenues (2024 Base Year)						
	Arkansas	\$/Million	\$6,494	\$920	\$4,985	\$9,084
	Illinois	\$/Million	\$3,221	\$395	\$2,563	\$4,174
	Iowa	\$/Million	\$16,238	\$3,048	\$11,500	\$21,828
	Kansas	\$/Million	\$11,879	\$1,620	\$9,008	\$15,876
	Minnesota	\$/Million	\$9,218	\$1,230	\$7,071	\$12,343
	Missouri	\$/Million	\$5,615	\$665	\$4,524	\$6,944
	Nebraska	\$/Million	\$14,351	\$2,480	\$10,306	\$18,855
	National	\$/Million	\$218,396	\$29,291	\$169,842	\$275,758

Table 4.4 Continued...**Real Government Payment Revenues
(2024 Base Year)**

Arkansas	\$/Million	\$679	\$240	\$382	\$1,219
Illinois	\$/Million	\$1,193	\$754	\$245	\$3,089
Iowa	\$/Million	\$1,638	\$940	\$585	\$4,294
Kansas	\$/Million	\$1,021	\$511	\$597	\$2,642
Minnesota	\$/Million	\$1,111	\$688	\$340	\$3,252
Missouri	\$/Million	\$747	\$362	\$269	\$1,789
Nebraska	\$/Million	\$1,063	\$600	\$593	\$2,925
National	\$/Million	\$20,389	\$10,434	\$12,465	\$54,175

Real Total Expenses (2024 Base Year)

Arkansas	\$/Million	\$10,701	\$1,066	\$8,223	\$12,013
Illinois	\$/Million	\$19,696	\$2,811	\$14,081	\$24,082
Iowa	\$/Million	\$31,730	\$4,909	\$21,622	\$40,155
Kansas	\$/Million	\$19,295	\$2,768	\$15,062	\$24,832
Minnesota	\$/Million	\$20,096	\$2,929	\$14,093	\$24,892
Missouri	\$/Million	\$11,448	\$1,526	\$8,455	\$13,052
Nebraska	\$/Million	\$23,673	\$3,503	\$17,441	\$28,742
National	\$/Million	\$425,224	\$43,055	\$337,594	\$507,961

Chapter 5 - Results

Results for each model type are described in the subchapters below with explanations of estimation procedures that describe the result processes for the regression coefficients as well as the projections from 2024 to 2032. The first model discussed is the seven-state panel mode, the second is the seven-state individual state model, and the third is the national model that uses state level delinquencies with national-level data as the independent variables. Baseline projections using the estimated coefficients are from RaFF fall 2024 state-level baseline projections between 2024 to 2032. The projected delinquency rate becomes the lagged delinquency rate variable for the following year. For example, the projected delinquency rate for 2024 then becomes the lagged delinquency rate for 2025's model.

5.1 Estimation Procedures

Models were estimated in Stata, a statistical data software (Statcorp, 2023). The seven-state panel model was estimated using a panel regression command with no constant and binary variables for each state. The individual state level models and the national level models used basic OLS regression model commands for each individual state.

To measure the model fit of each of these models we assessed the R^2 and RMSE of each model. The R^2 gives us the explanatory power of each variable while the RMSE gives us the error term for each model.

Time-series data raises concern about period-to-period correlation of the errors, i.e., autocorrelation. To test serial autocorrelation, the Durbin alternative test was conducted to assess whether significant autocorrelation was present within the models. Proïa (2013) cites the improvements made to Durbin alternative test and improvements in simplification of results and stronger convergence. The Stata code for the Durbin alternative test was found in the Stata

manual from Statacorp (2023). The test itself tests for “autocorrelation within the residuals” (Statacorp, 2023). If the p-value is less than 0.05 then there is serial autocorrelation and if it is above, then there is no serial autocorrelation. You cannot test panel models in this way. Below is **Table 5.1** of results for the Durbin alternative test. No regression model was found to have significant serial autocorrelation, however with a small sample size results can be misleading.

Table 5.1: Durbin Alternative Test for Autocollinearity

Model Type	Chi 2	p-value	Interpretation
Individual State Level Non-Real Estate Model			
Iowa Non-Real Estate	0.565	0.4524	No serial correlation
Kansas Non-Real Estate	0.350	0.5541	No serial correlation
Missouri Non-Real Estate	0.001	0.974	No serial correlation
Nebraska Non-Real Estate	0.947	0.3305	No serial correlation
Arkansas Non-Real Estate	0.223	0.6371	No serial correlation
Illinois Non-Real Estate	0.174	0.6762	No serial correlation
Minnesota Non-Real Estate	0.804	0.3698	No serial correlation
Individual State Level Real Estate Model			
Iowa Real Estate	0.612	0.4342	No serial correlation
Kansas Real Estate	2.405	0.1209	No serial correlation
Missouri Real Estate	0.006	0.9385	No serial correlation
Nebraska Real Estate	2.236	0.1348	No serial correlation
Arkansas Real Estate	3.711	0.0540	No serial correlation
Illinois Real Estate	0.139	0.7091	No serial correlation
Minnesota Real Estate	0.448	0.5034	No serial correlation
National Level Non-Real Estate Models			
Iowa Non-Real Estate	2.409	0.1206	No serial correlation
Kansas Non-Real Estate	0.084	0.7717	No serial correlation
Missouri Non-Real Estate	0.377	0.5394	No serial correlation
Nebraska Non-Real Estate	0.216	0.642	No serial correlation
Arkansas Non-Real Estate	0.709	0.3999	No serial correlation
Illinois Non-Real Estate	1.819	0.1774	No serial correlation
Minnesota Non-Real Estate	1.815	0.178	No serial correlation
National Level Real Estate Models			
Iowa Real Estate	2.241	0.1344	No serial correlation
Kansas Real Estate	2.617	0.1057	No serial correlation
Missouri Real Estate	0.189	0.6636	No serial correlation
Nebraska Real Estate	2.481	0.1152	No serial correlation
Arkansas Real Estate	1.286	0.2567	No serial correlation
Illinois Real Estate	0.350	0.5543	No serial correlation
Minnesota Real Estate	1.193	0.2748	No serial correlation

5.2 Seven-State Panel Model Results

When trying to determine how to compile the panel models originally regional models were created for Kansas and Nebraska, Missouri and Arkansas, as well as Illinois, Minnesota, and Iowa to see how the models behaved. Only the Kansas and Nebraska model exhibited results that made both economic sense and statistical sense when compared to the results of the seven-state panel model.

The results for the seven-state panel regression model presented in **Table 5.1**. All variables were in real values in billion dollars with the reference year as 2024. Results were as expected in the non-real estate model where each variable was statistically significant at the 95% level except for total expenses, which was not statistically different from zero. The panel models also include twelve independent variables, seven of which are binary variables to account for fixed effects at each individual state's level.

The overall model fit is demonstrated both in the graphs below and through key statistical metrics, including R^2 and Root Mean Squared Error (RMSE). The R^2 value of 0.926 suggests that the model explains approximately 92.6% of the variation in loan delinquency rates, indicating a strong fit. Additionally, the RMSE of 0.307 represents the average deviation between the model's predicted values and the actual loan delinquency rates. The overall model fit for the real estate model gave an R^2 of 0.966 and an RMSE of 0.231, indicating better statistical fit than the real estate model.

5.2.1 Non-real Estate Delinquency Model

The non-real estate crops revenue variable had a coefficient of -0.031, suggesting that a \$1 billion increase in real crop revenue is associated with a 0.03% decrease in loan delinquency rate. Similarly, the variable livestock revenue had a statistically significant coefficient of -0.086

at the 95% confidence level, indicating a negative relationship with loan delinquency rate. Total expenses had a positive coefficient but was not of statistical significance.

Lagged government payments had coefficient of -0.123 and were statistically significant at the 95% level. This result indicated producers used government payments received in the year prior to meet debt obligations of principal payments and interest payments in the current year. The lagged delinquency rate variable had the highest statistical significance of all the variables in the non-real estate model as well as the largest absolute value of any continuous variable. This is not surprising, as times of financial stress, or strength, in an industry tend to persist in the years following until there is a shift in the economic factors in the opposite direction.

In the pooled model, state-specific binary variables were included for each state because the model does not include an intercept variable. State binary variables capture fixed effects unique to each state, allowing the model to control unobserved factors that systematically influence loan delinquency rates across states.

The state binary coefficients represent the baseline loan delinquency rate for each state after accounting for the effects of other variables in the model. A positive coefficient suggests that, holding all else constant, the state has a higher underlying delinquency rate than average, while a negative coefficient indicates a relatively lower baseline delinquency rate than average. All state binary variables are statistically significant, meaning that these differences in baseline delinquency rates across states are important to account for.

For the pooled regression model, Iowa and Nebraska have the largest binary delinquency rate coefficients, with coefficients of 1.943 and 1.780, respectively, suggesting that these states experience persistently higher delinquency levels even after controlling for other factors. Missouri, with a coefficient of 0.854, has the lowest binary delinquency rate coefficient among

the states, indicating a comparatively lower structural risk of loan delinquency. Arkansas, Illinois, Kansas, and Minnesota binary delinquency rate coefficients fall in between, with coefficients ranging from 0.978 to 1.378, each reflecting its own distinct farm economy stress due to difference in agriculture and the risk attitudes of banks. These results highlight the structural differences in delinquency rates across states, which could be influenced by economic conditions, state-level policies, risk attitudes of banks, or differences in agricultural and financial markets.

The forward baseline projection for each model was derived from income and revenue baseline forecasts from RaFF datasets. Each state has its own projected baseline income and expense forecasts for the period between 2024 to 2032. For the forward-looking projections, the lagged dependent variable is simply the estimated prior year delinquency rate. For example, the estimated delinquency rate for 2024 is the lagged delinquency rate value for 2025 and so forth.

5.2.2 Real Estate Delinquency Model

The real estate model showed similar results to the non-real estate model. The crop revenue variable had a coefficient of -0.025 and was statistically significant at the 95% level. The Livestock revenue variable had a negative coefficient of -0.048 but it was not statistically significant. The total expense variable coefficient was not of the expected relationship with an effect of increasing real expense by \$1 billion causing real estate delinquency rate to drop by -0.005

The lagged government payment coefficient was statistically significant and of value of -0.166. This result is as expected indicating government payments increases the year prior increase cash flow for producers to pay off debt. The lagged delinquency rate was the most significant coefficient and had the largest absolute value of any continuous variable.

Table 5.2: 7-State Pooled Panel Regression Results (Equations 1 & 2)

7-State Pooled Model		
Variable	Non-Real Estate	Real Estate
Intercept	n/a	n/a
Crop Revenues	-0.031** (0.010)	-0.025** (0.005)
Livestock Revenues	-0.086** (0.021)	-0.048 (0.025)
Total Expenses	0.021 (0.024)	-0.005 (0.021)
Government Payment Revenues Lagged	-0.123** (0.024)	-0.166** (0.036)
Lagged Delinquency Rate	0.574*** (0.062)	0.833*** (0.023)
Arkansas Dummy	0.997** (0.184)	0.857** (0.192)
Illinois Dummy	0.978** (0.330)	1.091** (0.360)
Iowa Dummy	1.943** (0.441)	1.825** (0.539)
Kansas Dummy	1.378** (0.286)	1.227** (0.335)
Minnesota Dummy	1.370** (0.303)	1.274** (0.341)
Missouri Dummy	0.854** (0.183)	0.798** (0.200)
Nebraska Dummy	1.780** (0.339)	1.440** (0.539)
RMSE	0.30745	0.23210
R ²	0.9256	0.9662
No. Observations	126	126

Figure 5.1: Iowa Non-Real Estate Panel Results Graph

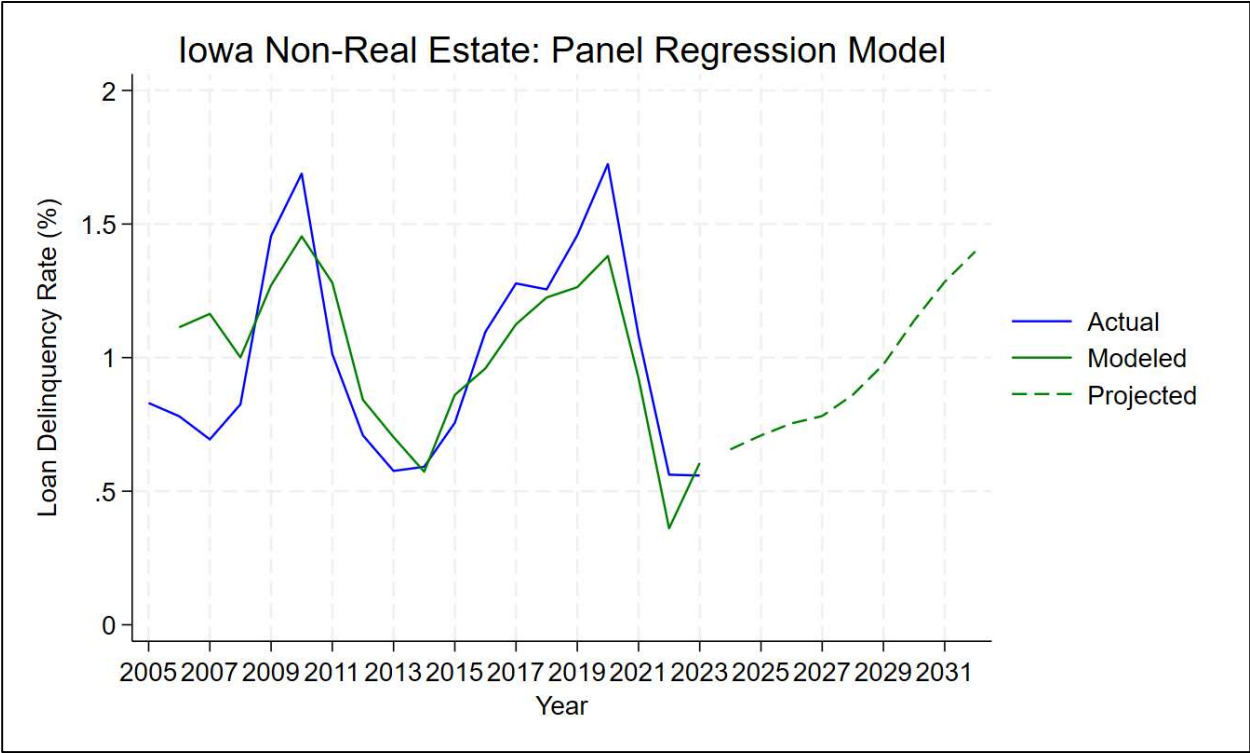


Figure 5.2: Iowa Real Estate Panel Results Graph

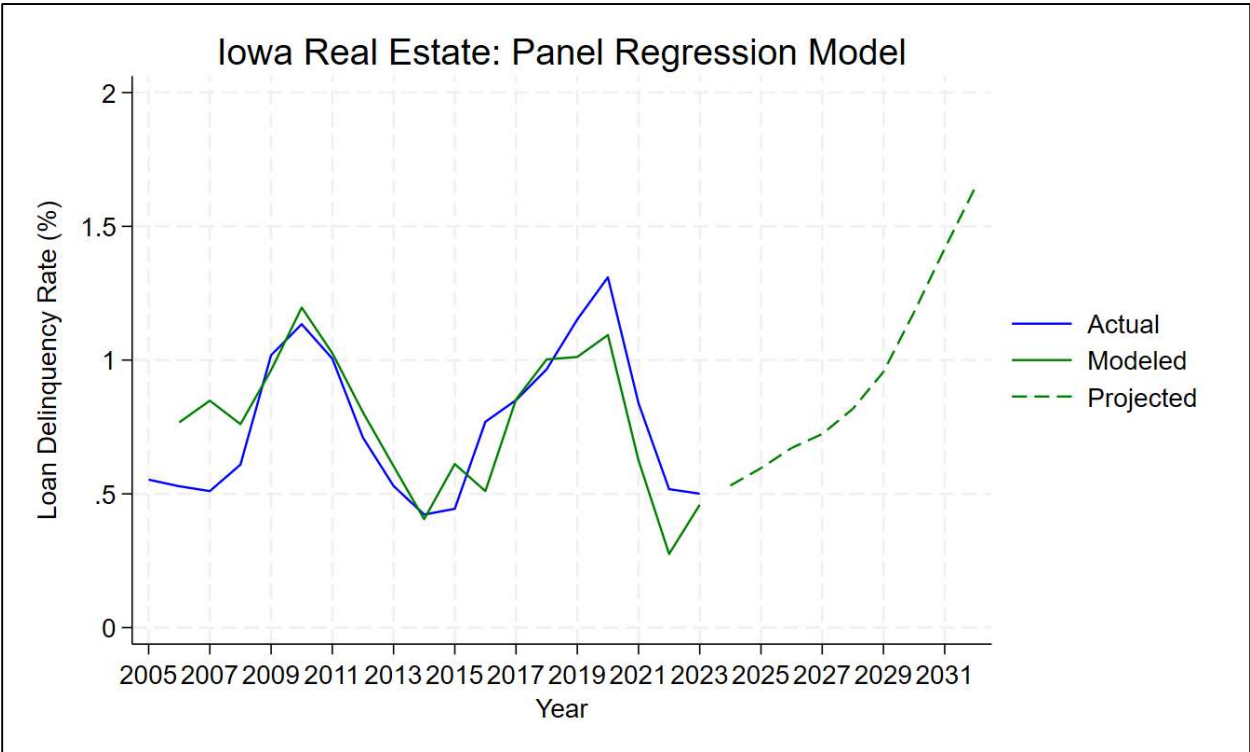


Figure 5.3: Kansas Non-Real Estate Panel Results Graph

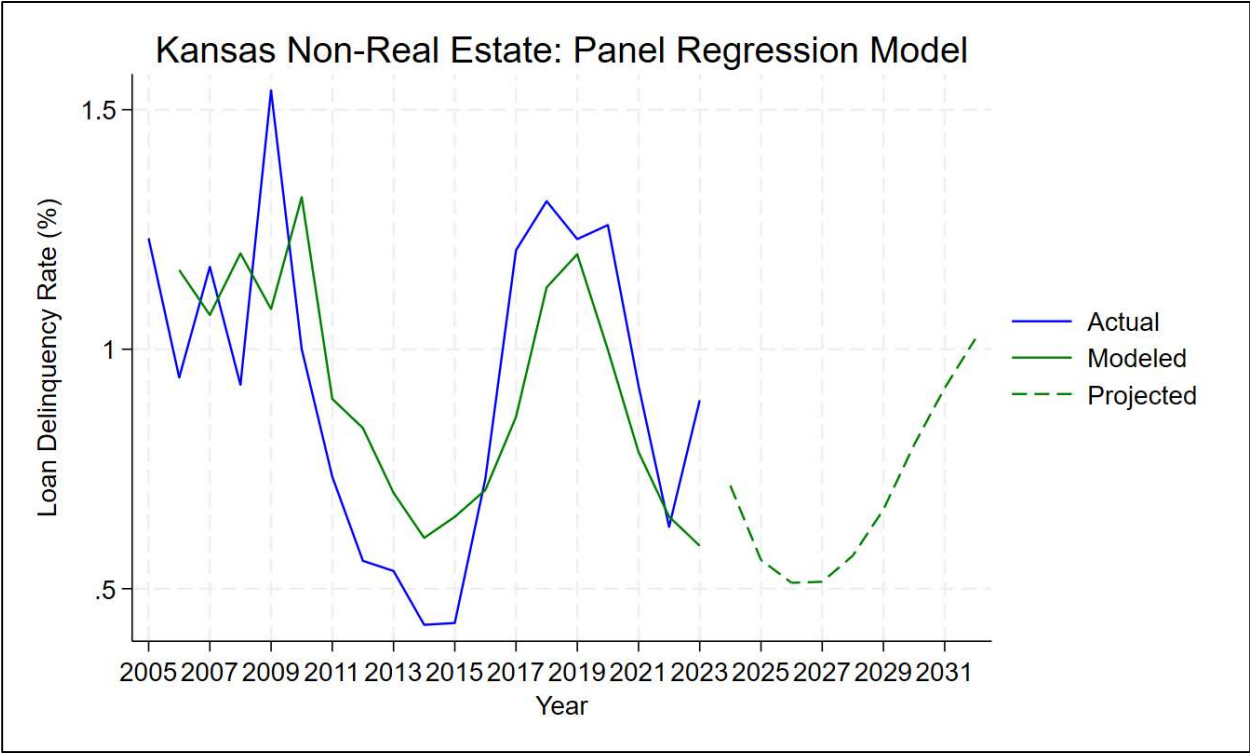


Figure 5.4: Kansas Real Estate Panel Results Graph

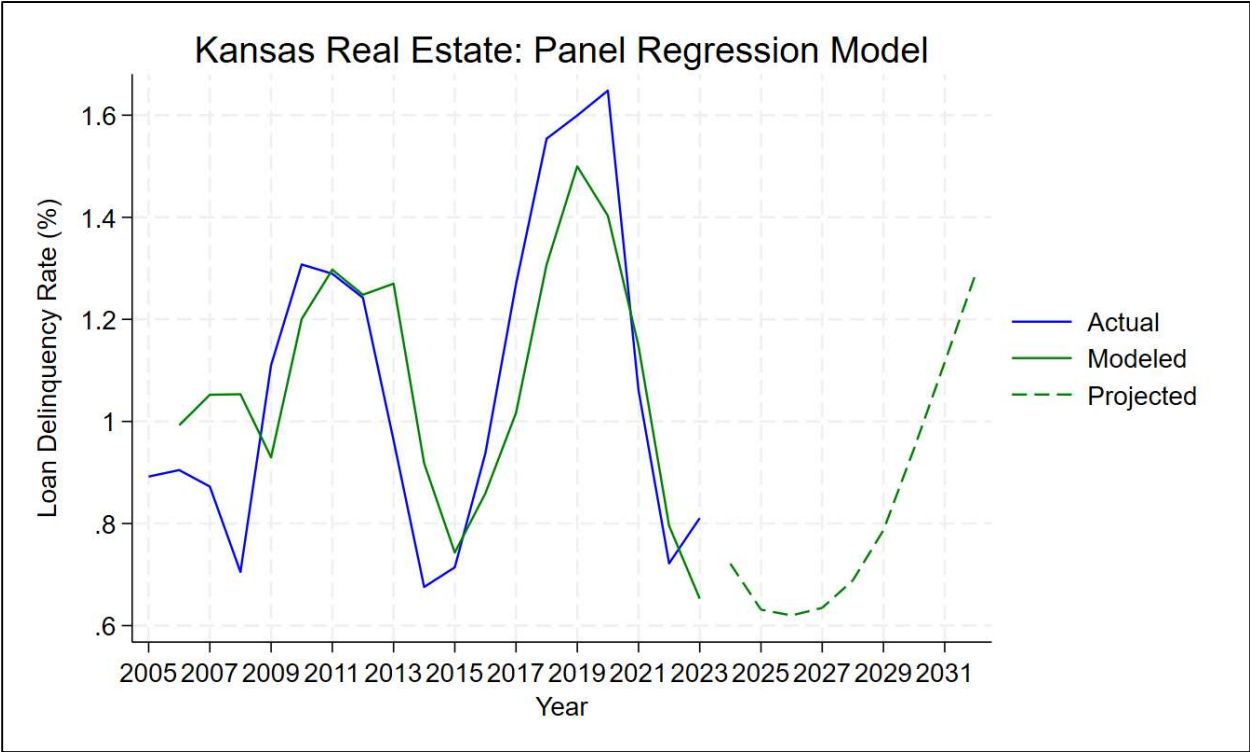


Figure 5.5: Missouri Non-Real Estate Panel Results Graph

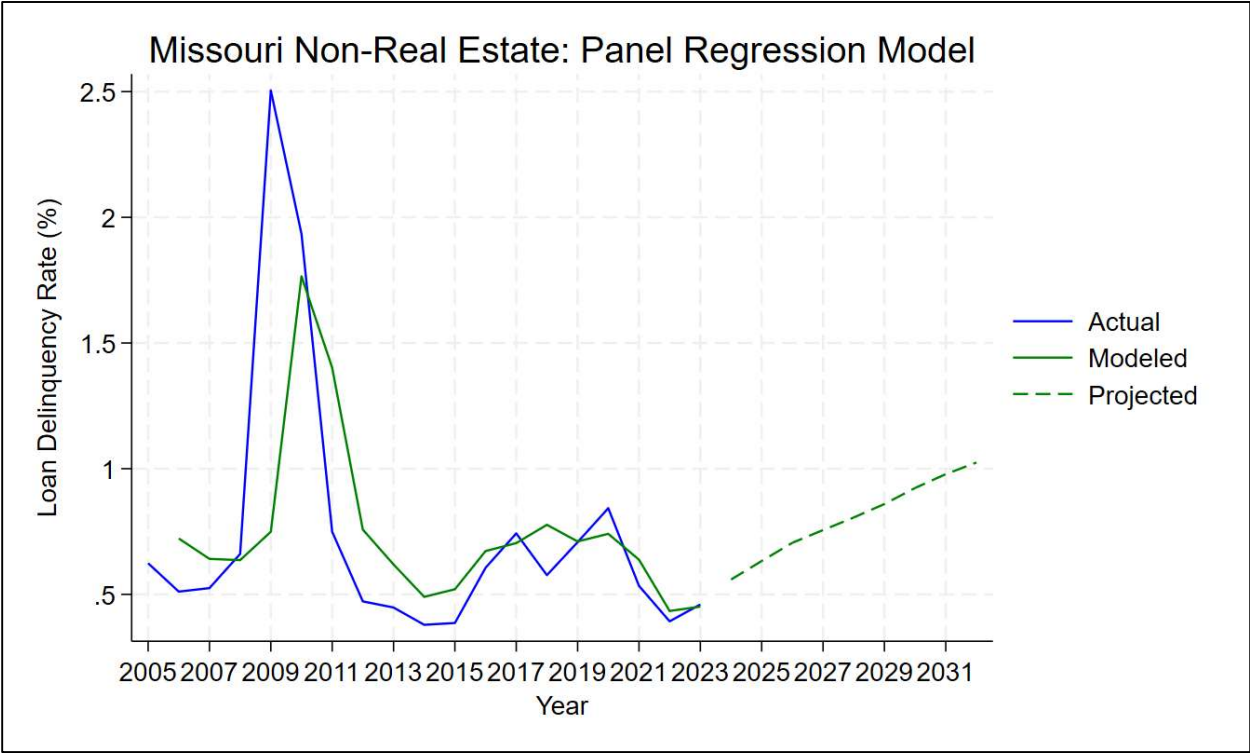


Figure 5.6: Missouri Real Estate Panel Results Graph

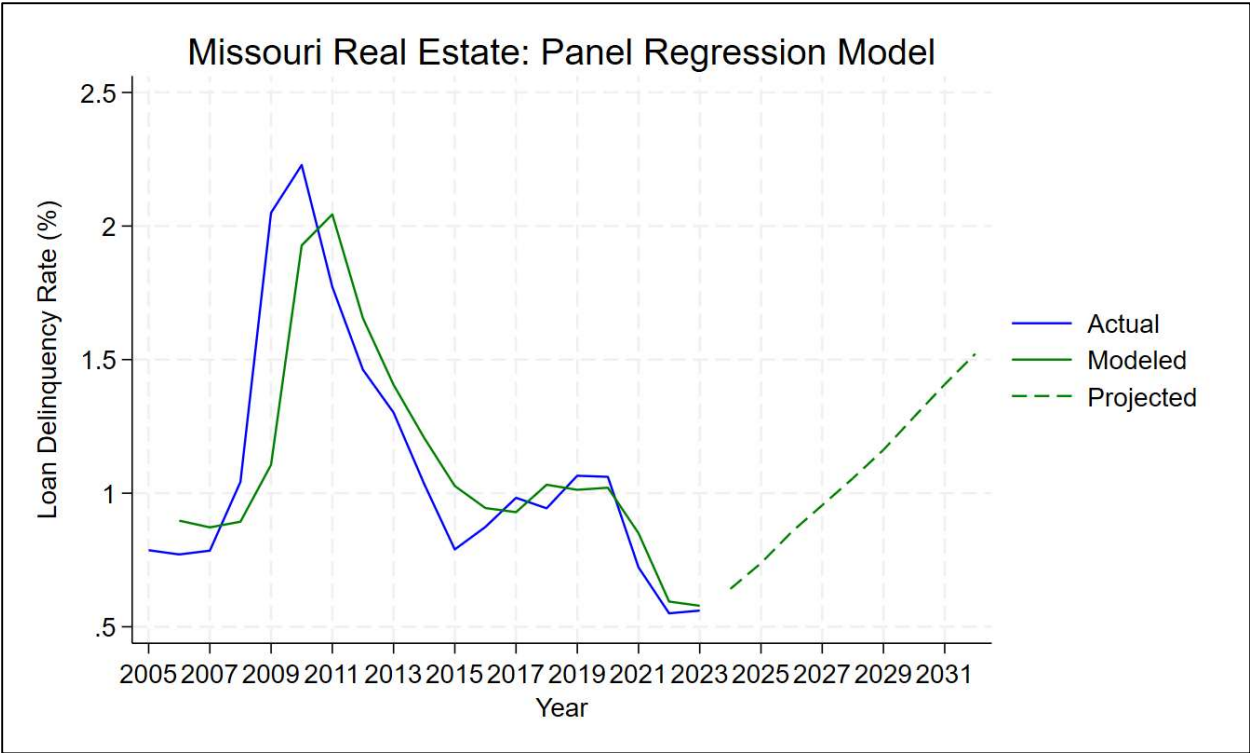


Figure 5.7: Nebraska Non-Real Estate Panel Results Graph

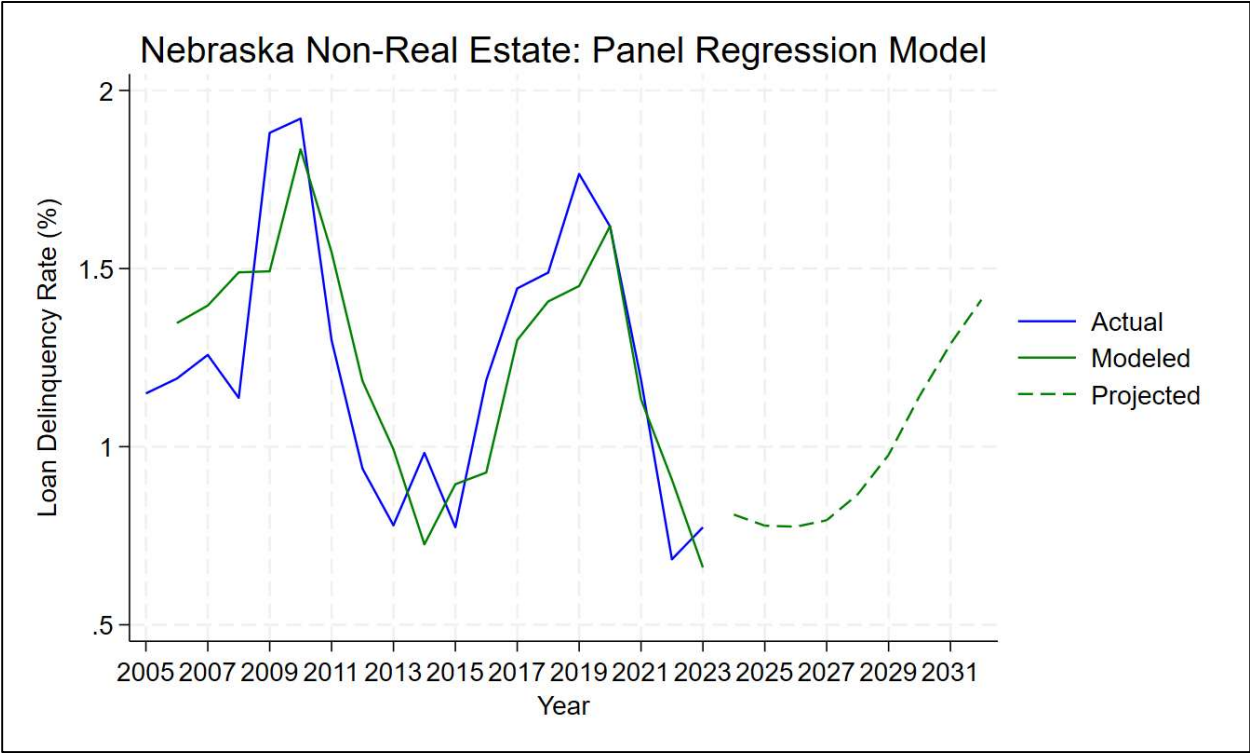


Figure 5.8: Nebraska Real Estate Panel Results Graph

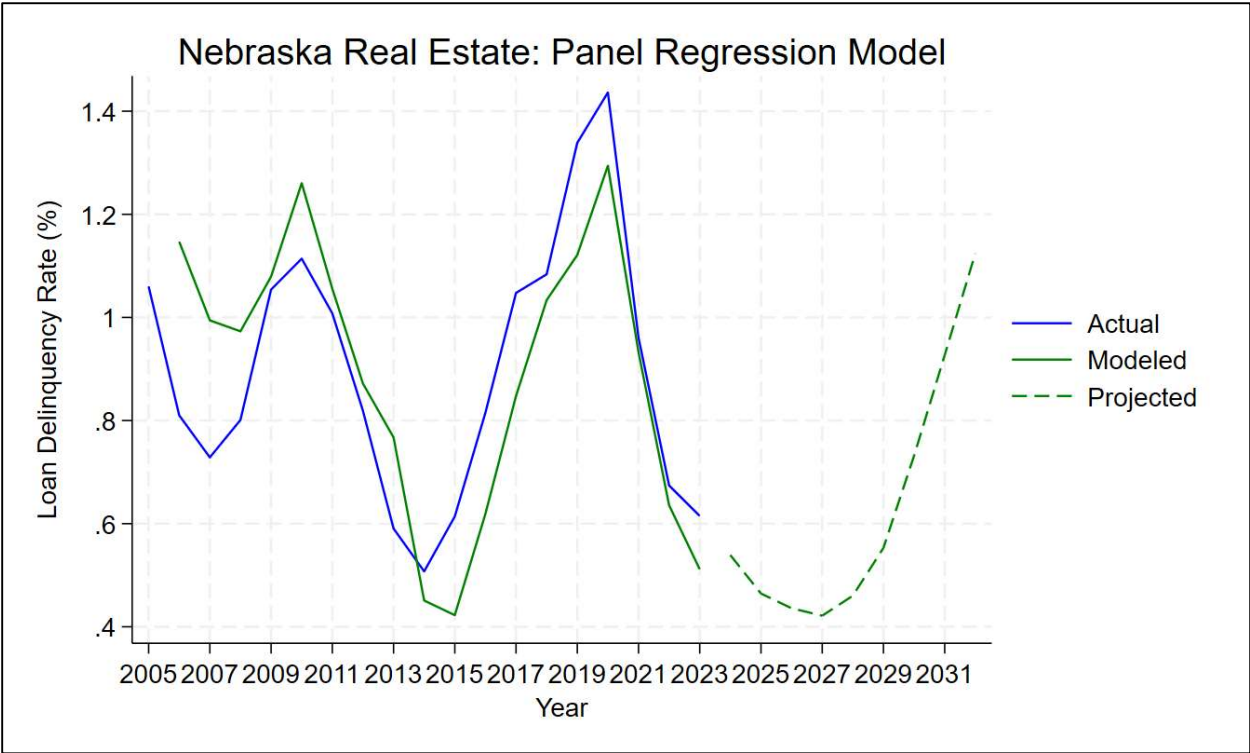


Figure 5.9: Arkansas Non-Real Estate Panel Results Graph

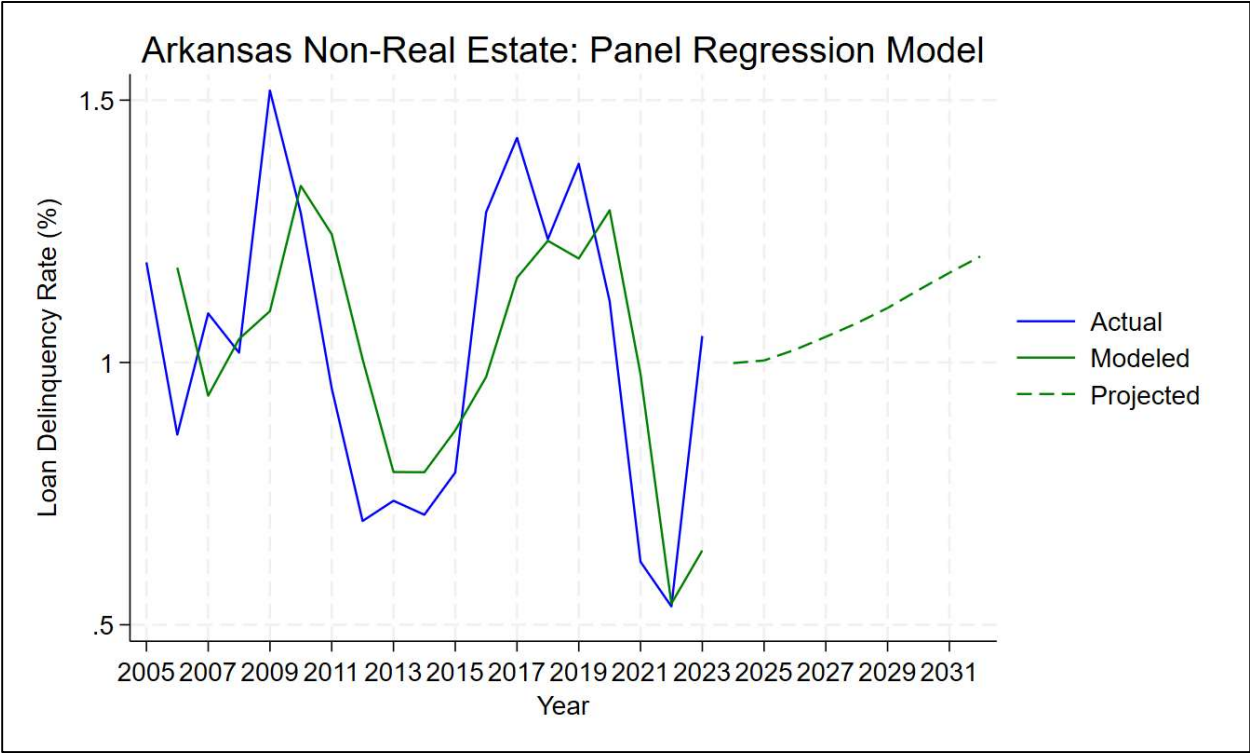


Figure 5.10: Arkansas Real Estate Panel Results Graph

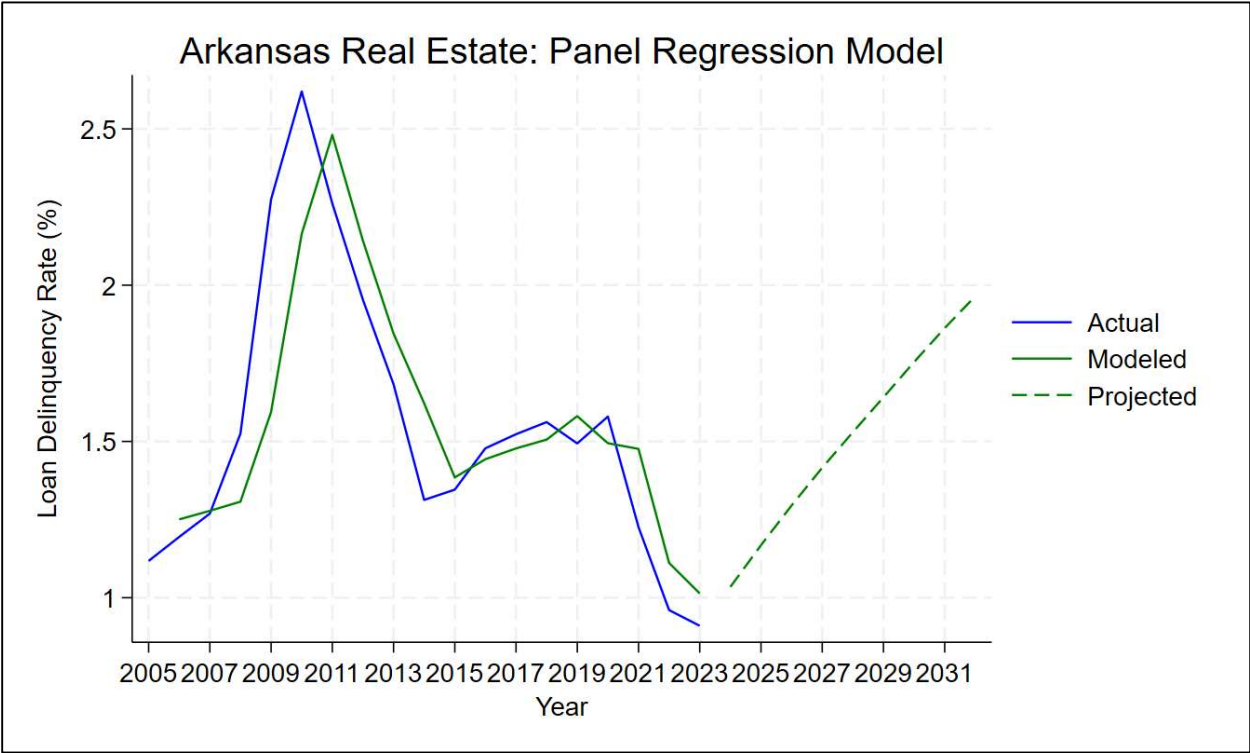


Figure 5.11: Illinois Non-Real Estate Panel Results Graph

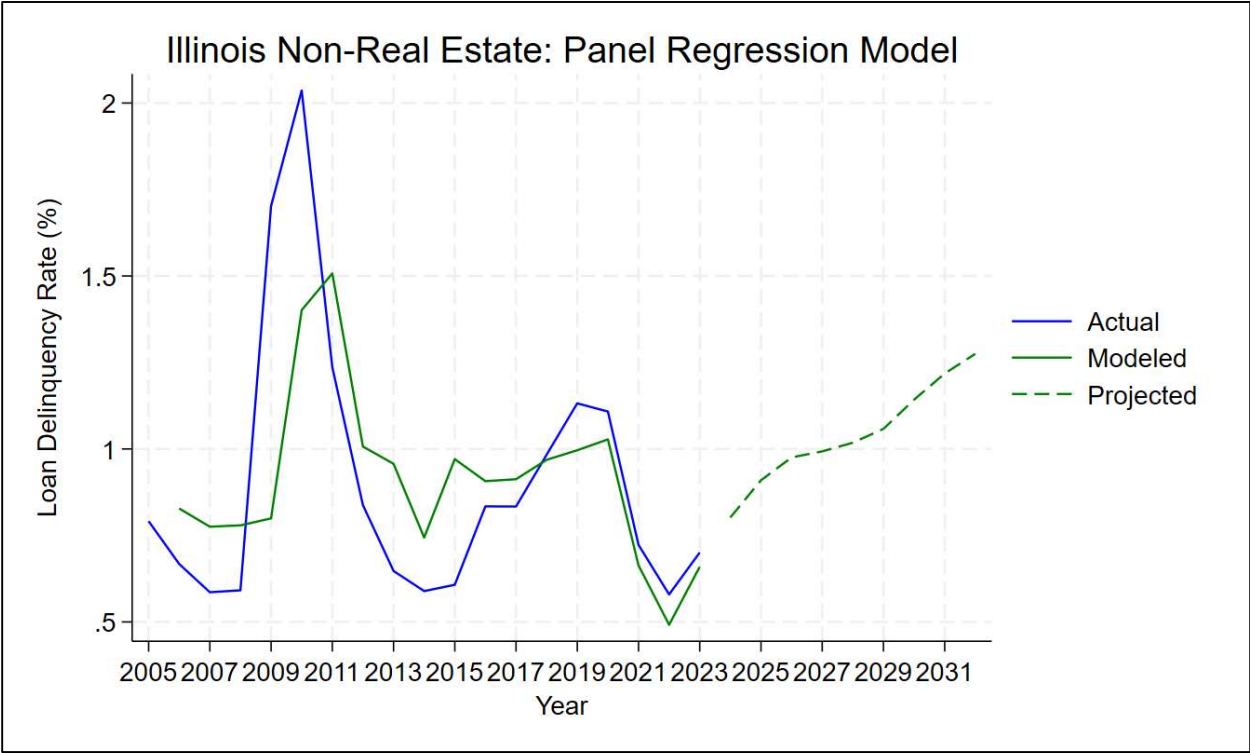


Figure 5.12: Illinois Real Estate Panel Results Graph

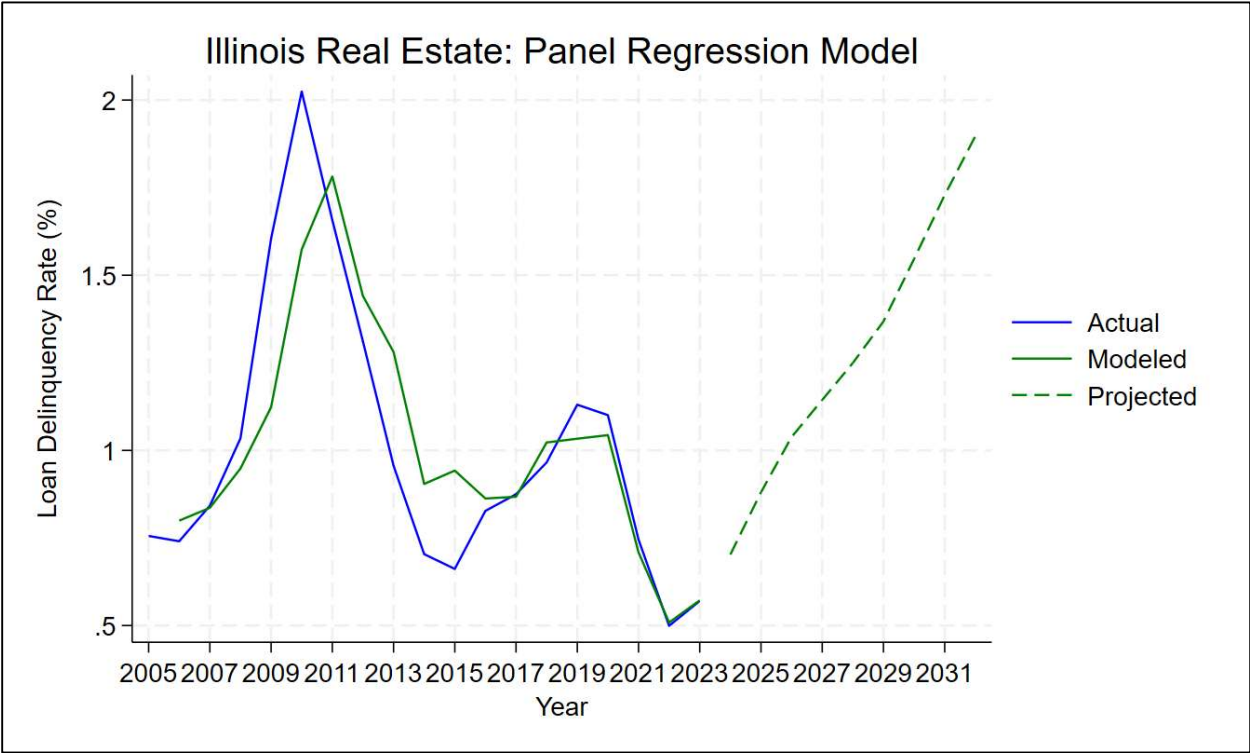


Figure 5.13: Minnesota Non-Real Estate Panel Results Graph

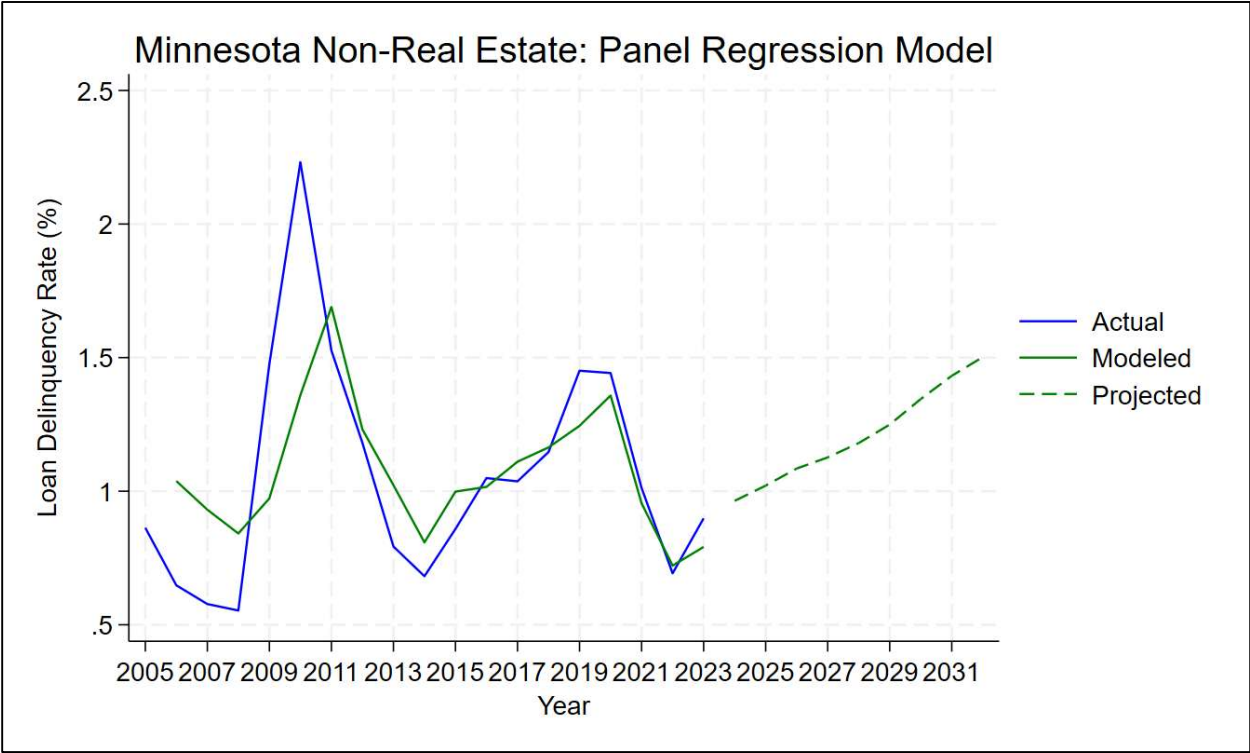
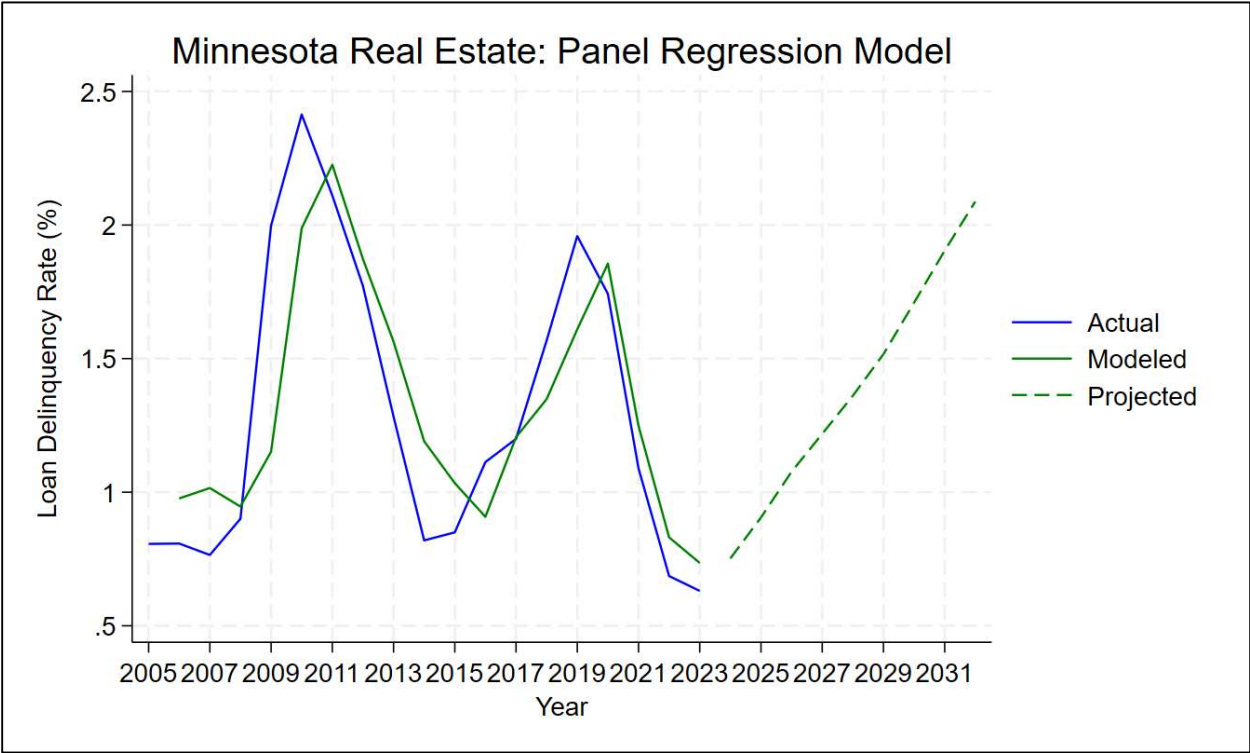


Figure 5.14: Minnesota Real Estate Panel Results Graph



5.3 Seven-State Individual Model Results

The second state level model that followed equations three and four yielded results that also made economic sense besides a few exceptions, specifically in the Missouri models. Results for the individual state level regressions can be seen in **Table 5.2**.

Table 5.3: Individual State Level Model Results (Equations 3 & 4)

Variable	Individual State Level Models							
	Iowa Non- Real Estate	Iowa Real Estate	Kansas Non- Real Estate	Kansas Real Estate	Missouri Non-Real Estate	Missouri Real Estate	Nebraska Non-Real Estate	Nebraska Real Estate
Intercept	0.955	0.866	1.263	1.113	1.721	2.777	1.721	0.516
Crop Revenues	-0.042** (0.016)	-0.023* (0.011)	-0.030 (0.053)	-0.020 (0.045)	0.180 (0.158)	0.121 (0.075)	-0.068* (0.033)	-0.049** (0.020)
Livestock Revenues	-0.119** (0.037)	-0.067 (0.025)	-0.139 (0.088)	-0.077 (0.069)	-0.440 (0.255)	-0.300** (0.129)	-0.119* (0.066)	-0.058* (0.041)
Total Expenses	0.067** (0.026)	0.027 (0.018)	0.058 (0.056)	0.014 (0.044)	-0.144 (0.143)	-0.103 (0.064)	0.065 (0.056)	0.048 (0.033)
Government Payment Revenues Lagged	-0.119* (0.060)	-0.100** (0.042)	-0.052 (0.152)	-0.228* (0.119)	-0.376 (0.359)	-0.430** (0.184)	-0.149 (0.101)	-0.222** (0.080)
Lagged Delinquency Rate	0.836*** (0.151)	0.947*** (0.151)	0.520* (0.260)	0.927*** (0.216)	0.203 (0.260)	0.652*** (0.136)	0.574** (0.224)	1.034*** (0.227)
RMSE	0.2096	0.1436	0.2777	0.2179	0.2461	0.2412	0.2461	0.1490
R ²	0.7991	0.8113	0.4914	0.6693	0.7131	0.8226	0.7131	0.7671
No. Observations	18	18	18	18	18	18	18	18

Table 5.4: Individual State Level Model Results (Equations 3 & 4) Continued...

Individual State Level Models						
Variable	Arkansas Non-Real Estate	Arkansas Real Estate	Illinois Non-Real Estate	Illinois Real Estate	Minnesota Non-Real Estate	Minnesota Real Estate
Intercept	1.991	2.277	2.271	2.366	1.704	2.558
Crop Revenues	-0.179 (0.112)	-0.045 (0.111)	0.020 (0.029)	0.004 (0.016)	-0.025 (0.038)	-0.027 (0.031)
Livestock Revenues	-0.045 (0.090)	-0.140 (0.102)	-0.528 (0.346)	-0.278 (0.194)	-0.207 (0.127)	-0.276** (0.102)
Total Expenses	0.017 (0.112)	-0.050 (0.130)	-0.021 (0.061)	-0.061 (0.035)	0.052 (0.062)	0.041 (0.050)
Government Payment Revenues Lagged	-0.527 (0.371)	-0.415 (0.326)	-0.152 (0.158)	-0.222** (0.088)	-0.179 (0.123)	-0.276** (0.099)
Lagged Delinquency Rate	0.381 (0.329)	0.793** (0.220)	0.626** (0.192)	0.930*** (0.113)	0.709** (0.207)	0.867*** (0.132)
RMSE	0.2435	0.2629	0.3016	0.1645	0.3393	0.2749
R ²	0.5271	0.7649	0.6143	0.8845	0.5627	0.8302
No. Observations	18	18	18	18	18	18

5.3.1 Non-Real Estate Delinquency Model

The non-real estate models for each individual state were mostly as expected except for a few states. For the Iowa non-real estate model all signs were as expected and statistically significant by a minimum of the 90% level. The overall R² was 0.799, indicating a strong statistical fit and the RMSE was 0.210. The crop revenues had a coefficient of -0.042, and as a reminder all farm income variables were in billions so this indicates an increase in one billion dollars of crop revenues would result in a decrease of the expected delinquency rate by 0.042%. Livestock revenues had a coefficient of -0.119, total expenses 0.067, lagged government payments -0.119, and the lagged delinquency rate was 0.836. The projected delinquency rates in

Figure 5.15 from 2024 to 2032 for this model showed a slight decrease from 2024 to 2027 before increasing back to similar delinquency rates seen in 2023 by 2032.

The overall model fit for the non-real estate delinquency rate model for Kansas gave an R^2 of 0.491 and an RMSE of 0.278. The Kansas non-real estate model did not produce any statistically significant results except for the lagged delinquency rate which differs from the Iowa model. However, it did report coefficients with signs as expected. The crop revenues coefficient was -0.030, livestock revenues -0.139, total expenses 0.058, lagged government payments -0.052, and the lagged delinquency rate 0.520 which was significant at the 90% level. What this tells us is that the lagged delinquency rate or times of financial struggle or strength play the largest role in the non-real estate delinquency rates within the state of Kansas. In the projected delinquency rates in **Figure 5.17** we see similar projections to the Iowa non-real estate model in that delinquency rates are projected to drop over the first few years before increasing to 2023 levels by 2032.

The Missouri individual state models did not fully align with economic expectations and reported an R^2 of 0.490 and an RMSE of 0.470 which was the highest RMSE of all individual state level models. In the non-real estate model, crop revenues (0.180) reported a positive coefficient, suggesting that higher crop revenues were associated with increased delinquency rates, which contradicts conventional expectations. Similarly, total expenses (-0.144) showed an inverse relationship with delinquency rates, an unexpected result that does not align with economic intuition. The other coefficients—livestock revenues (-0.440), lagged government payments (-0.376), and lagged delinquency rates (0.203)—followed more expected trends. However, none of the variables in Missouri's non-real estate model were statistically significant, limiting the model's explanatory power. The projected delinquency rates can be seen in **Figure**

5.19 from 2024 to 2032 for the Missouri model show an increase in delinquency rates from around 0.5% in 2023 to roughly 1.6% by 2032.

Nebraska's non-real estate model demonstrated strong predictive accuracy, with an R^2 of 0.713, indicating that 71.31% of the variation in non-real estate loan delinquencies can be explained by the model's variables. Additionally, the RMSE of 0.246 suggests a relatively low level of forecast error, reinforcing the model's reliability in predicting delinquency rates.

The model also resulted in values that made both economic sense and had three of the five variables showing statistical significance. Crop revenues coefficient was -0.068 (significant at the 90% level), livestock revenues -0.119 (significant at the 90% level), total expenses 0.065, lagged government payments -0.149, and the lagged delinquency 0.547 (significant at the 95% level). The non-real estate model projections for Nebraska in **Figure 5.21** from 2024 to 2032 show a stabilizing trend in the first few years until around 2027 before increasing to nearly 1.5% in 2032.

Arkansas non-real estate model results did not stray from expected results but did not report any variables with any statistical significance. Crop revenues -0.179, livestock revenues -0.045, total expenses 0.017, lagged government payments -0.527, and lagged delinquency coefficient of 0.381. The RMSE of 0.244 and R^2 of 0.527 only further exhibit the poor predictive power of this model for the state of Arkansas with these variables. Projected delinquency rates in **Figure 5.23** for Arkansas show a sharp increase in delinquency rates in the years given for the baseline projections from 2024 to 2032 by rising from around 1% in 2024 to just over 1.6% in 2032. The projection of 1.6% would be the highest delinquency rate observed in Arkansas non-real estate during the model period.

The Illinois non-real estate model produced mixed results as the model demonstrated moderate predictive power, with an R^2 of 0.614, meaning it explained approximately 61.43% of the variation in non-real estate loan delinquencies. The RMSE of 0.302 indicates a reasonable level of forecast accuracy. Some coefficients aligned with expectations while others did not. Notably, crop revenues (0.020) and total expenses (-0.021) reported signs opposite of what was anticipated, suggesting that increases in crop revenues were associated with higher delinquency rates, while higher expenses correlated with lower delinquency rates. However, these variables were not statistically significant. In contrast, livestock revenues (-0.528), lagged government payments (-0.152), and lagged delinquency rates (0.626) had coefficients that followed the expected economic relationships, with only lagged delinquency rates being statistically significant at the 95% level. For Illinois projected delinquency rates in **Figure 5.25**, they are projected to rise from around .75% in 2024 to around 1.6% in 2032.

The Minnesota non-real estate model explained 56.3% of the variation in delinquency rates ($R^2 = 0.563$) and had an RMSE of 0.339, indicating a poor level of accuracy relative to the other state models. The regression produced expected variable coefficients, with crop revenues (-0.025) and livestock revenues (-0.207) negatively associated with delinquency rates, while total expenses (0.052) and lagged government payments (-0.179) followed anticipated trends. The only statistically significant variable was lagged delinquency rates (0.709) at the 95% level, highlighting the persistence of delinquency rates over time. The Minnesota projected delinquency rates in **Figure 5.27** are expected to rise from just under 1% in 2024 to nearly 1.75% by 2032 based on the baseline projections used in the model.

5.3.2 Real Estate Delinquency Model

The Iowa real estate model reported an overall R^2 of 0.811 indicated that the real estate model is a better statistical fit than the non-real estate model. A lower RMSE of 0.144 also told a similar story as well. The model variables performed similarly in that all variables resulted in expected signs of coefficients, however there were not as many statistically significant variables with only crop revenues (90% level), government payment revenues (95% level) and the lagged delinquency rates (99% level) being statistically significant. The crop revenues coefficient was -0.023, livestock revenues -0.067, total expenses 0.027, lagged government payments -0.100, and lagged delinquency rate 0.947. **Figure 5.16** shows the actual, modeled and projected loan delinquency rates until 2032. The projected delinquency rates follow a very similar trend to the non-real estate projections with a drop in delinquency rates until 2028 before increasing to pre 2023 delinquency rates levels by 2032.

Our Kansas real estate model produced results that were more statistically significant relative to the non-real estate model and gave an R^2 of 0.670 and RMSE of 0.218. Coefficients for the variables were as follows: crop revenues -0.020, livestock revenues -0.077, total expenses 0.014, lagged government payments -0.228 and lagged delinquency rates 0.927. The government payment lagged variable was statistically significant at the 90%, meanwhile the lagged delinquency rate was statistically significant at the 99% level. **Figure 5.18** shows the projected delinquency rates for the real estate model in Kansas, which are very similar to the non-real estate model as well. What is projected is a decrease in delinquency rates until roughly 2028 before seeing an increase in delinquency rates through 2032.

The real estate model demonstrated for Missouri gave a stronger fit compared to its non-real estate model, with an R^2 of 0.823, indicating it explained 82.3% of the variation in

delinquency rates, significantly higher than the non-real estate model. However, while the RMSE of 0.241 showed improved accuracy compared to the non-real estate model, it remained relatively high in comparison to other real estate models. The Missouri real estate model produced similar coefficient results, with both crop revenues (0.121) and total expenses (-0.103) again displaying unexpected signs. However, livestock revenues (-0.300) and lagged government payments (-0.430) were statistically significant at the 95% level, while lagged delinquency rates (0.652) were statistically significant at the 99% level, reinforcing the persistence of delinquency trends over time. **Figure 5.20** illustrates Missouri's projected delinquency rates, which are projected to have a steep rise from around 0.5% in 2023 to over 2.5% by 2032.

The R^2 for the real estate model for Nebraska was 0.767 and had a relatively low RMSE of 0.149 compared to the other states. Nebraska's real estate model reported values like the non-real estate model but with more statistical significance with four of the five variables showing statistical significance. Crop revenues -0.049 (significant at the 95% level), livestock revenues -0.058 (significant at the 90% level), total expenses 0.048, lagged government payment revenues -0.222 (significant at the 95% level), and lagged delinquency rates 1.034 (significant at the 99% level). Of all the individual state level models the Nebraska real estate model lagged delinquency rate exhibited the largest absolute value of any coefficient indicating financial stress or strength plays an exceptionally large role in real estate delinquencies. For the Nebraska real estate model projections, delinquency rates are projected to remain near 0.6% until around 2029 before increasing closer to 1% by 2032. This can be seen in **Figure 5.22**.

The real estate model for Arkansas reported an R^2 of 0.765 which shows a significant difference against the non-real estate model in explaining the variation in real estate delinquencies while the RMSE was higher at 0.263 when compared to the non-real estate model.

Coefficient results were as expected except for the total expense variable of -0.050, indicating that as expenses rose the delinquency rates were to decrease. Other than the results were as expected with the lagged delinquency rate being the only statistically significant variable at the 95% level. Coefficient results are as follows: crop revenues -0.045, livestock revenues -0.140, lagged government payments -0.415, and lagged delinquency rates 0.793. **Figure 5.24** shows the projected delinquency rates for Arkansas are projected to increase significantly from just below 1% to over 3% by 2032.

Despite only two variables achieving statistical significance, the real estate model for Illinois had the highest R^2 . 0.885, among all individual state-level models, indicating strong explanatory power. Additionally, the model's RMSE of 0.165 was among the lowest, suggesting a high degree of predictive accuracy. The Illinois real estate model showed similar trends to its non-real estate model, with crop revenues (0.004) and total expenses (-0.061) again exhibiting opposite signs from expectations and neither reaching statistical significance. However, livestock revenues (-0.278), lagged government payments (-0.222), and lagged delinquency rates (0.930) aligned with anticipated relationships. Among these, lagged government payments were statistically significant at the 95% level, while lagged delinquency rates were highly significant at the 99% level, emphasizing the persistence of delinquency trends over time. Projected values can be seen in **Figure 5.26** which show a sharp increase in delinquency rates from around 0.5% in 2023 to over 3% by 2032.

The Minnesota real estate model produced similar results to the non-real estate model. It reported an R^2 of 0.830 and an RMSE of 0.275. Although it did have three statistically significant variables: livestock revenues (-0.276) and lagged government payments (-0.276) at the 95% level and lagged delinquency rates (0.867) at the 99% level. Crop revenues (-0.027) and

total expenses (0.041) followed expected trends but were not statistically significant. **Figure 5.28** shows the Minnesota delinquency rates by year and shows projections increasing from over 0.75% in 2023 to just over 2.5% by 2032.

Figure 5.15: Iowa Non-Real Estate Individual State Model Results Graph

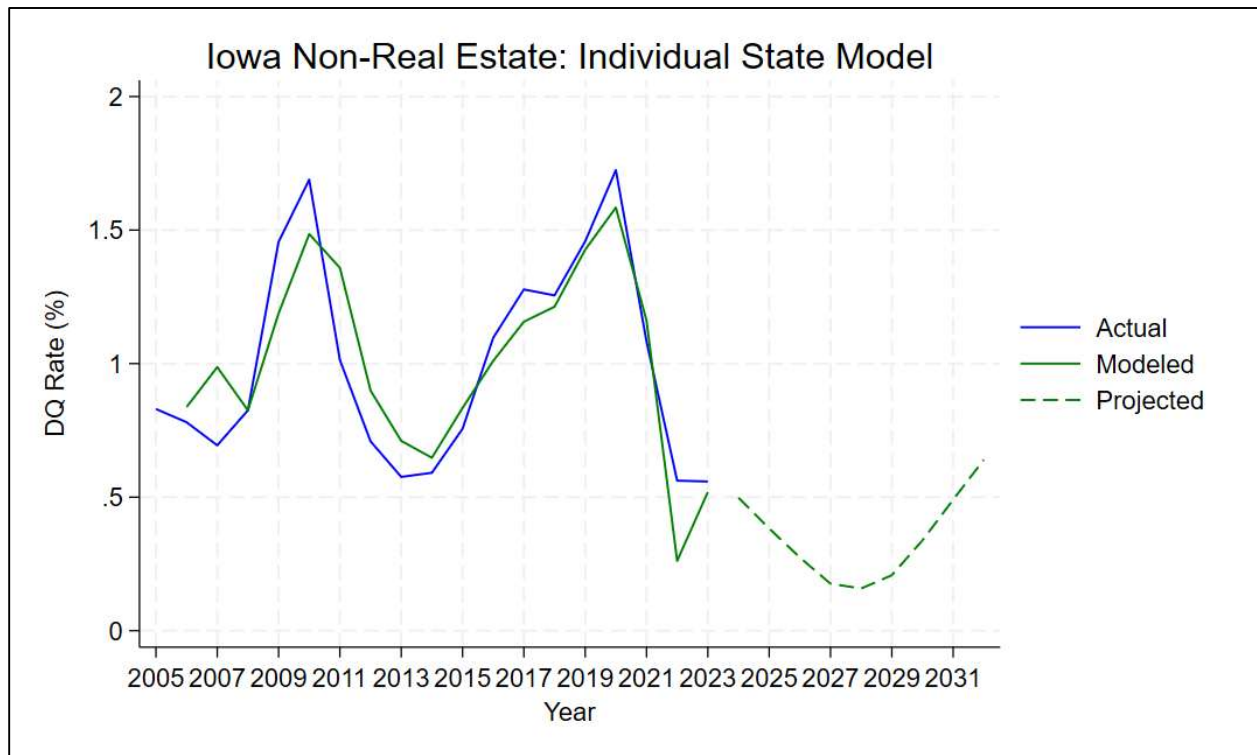


Figure 5.16: Iowa Real Estate Individual State Model Results Graph

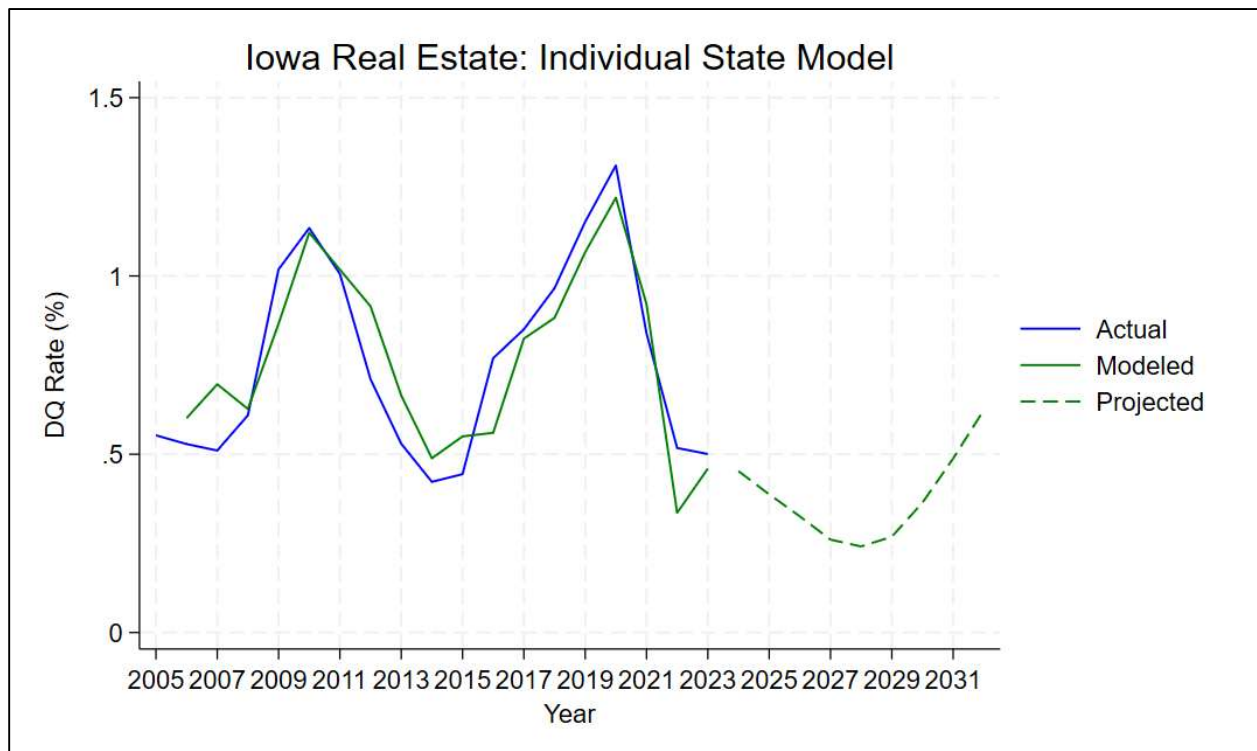


Figure 5.17: Kansas Non-Real Estate Individual State Model Results Graph

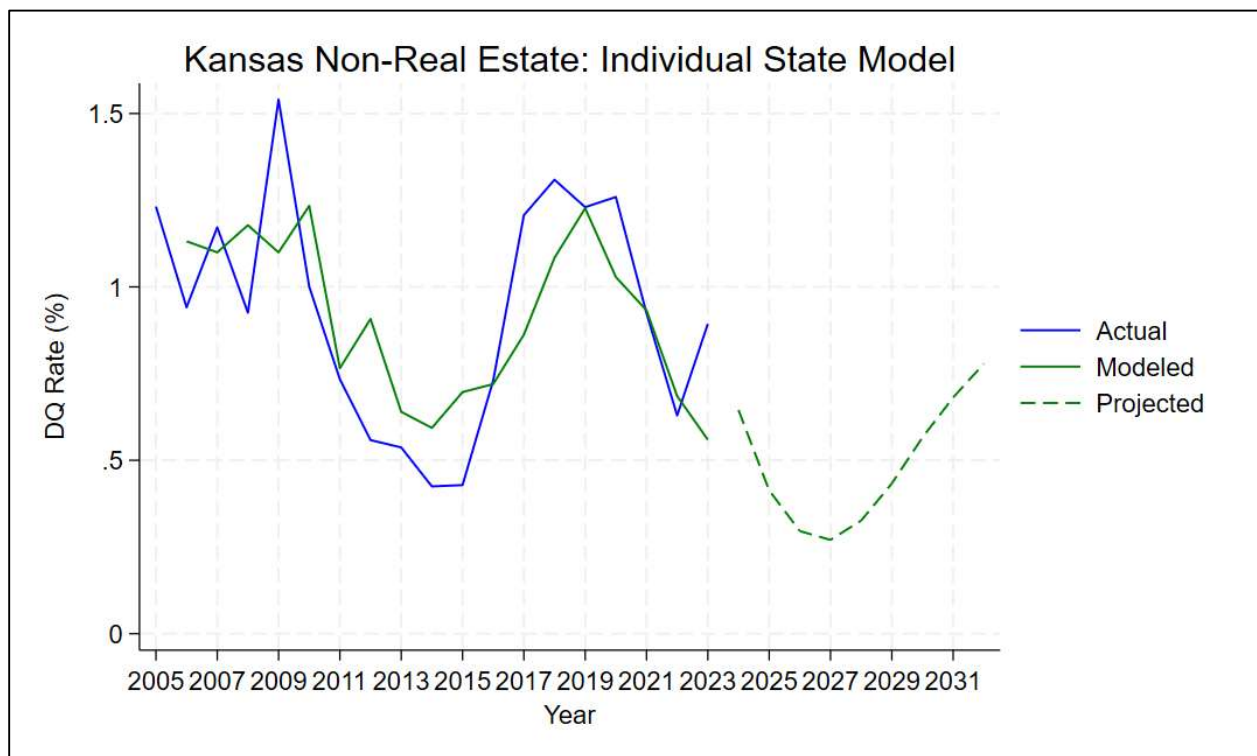


Figure 5.18: Kansas Real Estate Individual State Model Results Graph

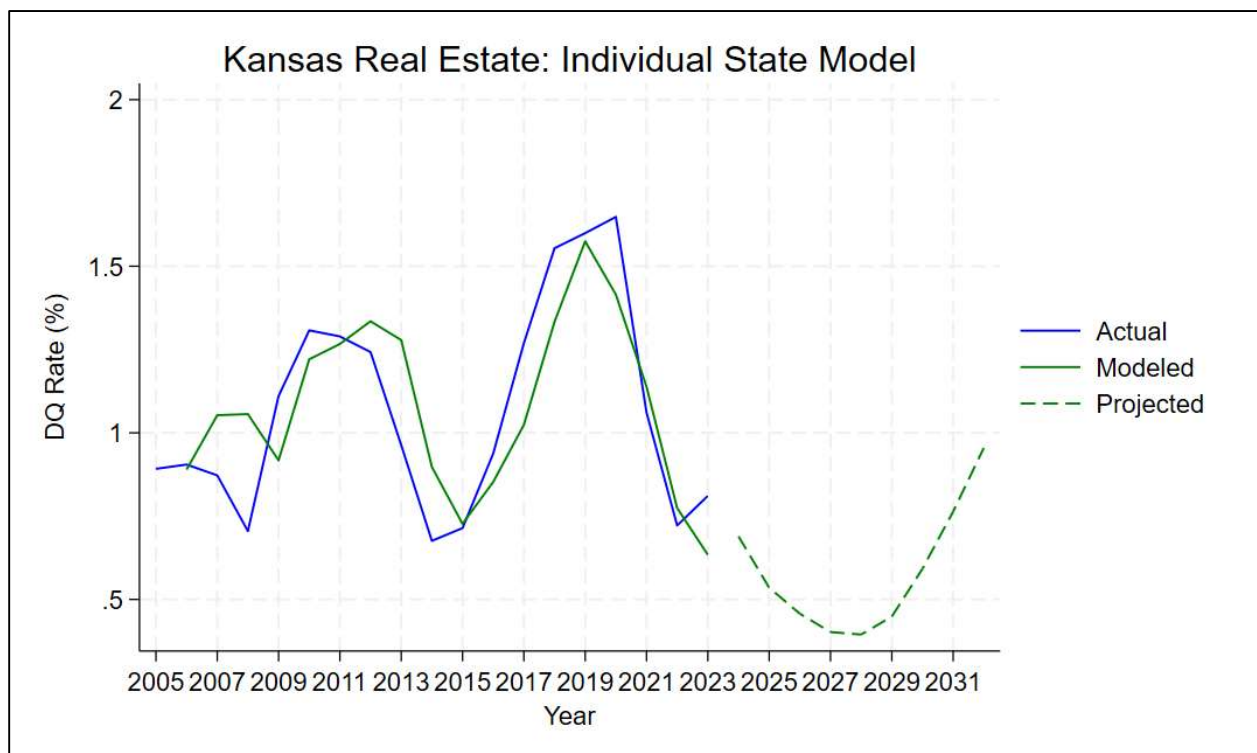


Figure 5.19: Missouri Non-Real Estate Individual State Model Results Graph

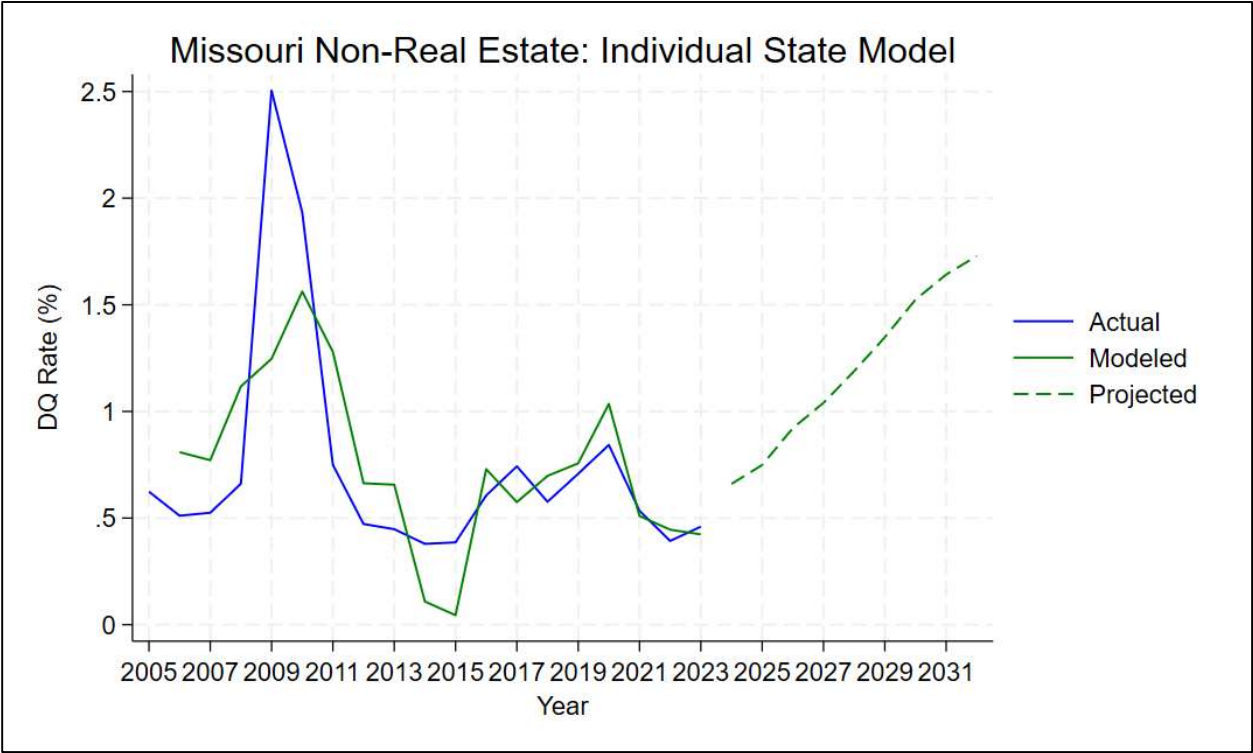


Figure 5.20: Missouri Real Estate Individual State Model Results Graph

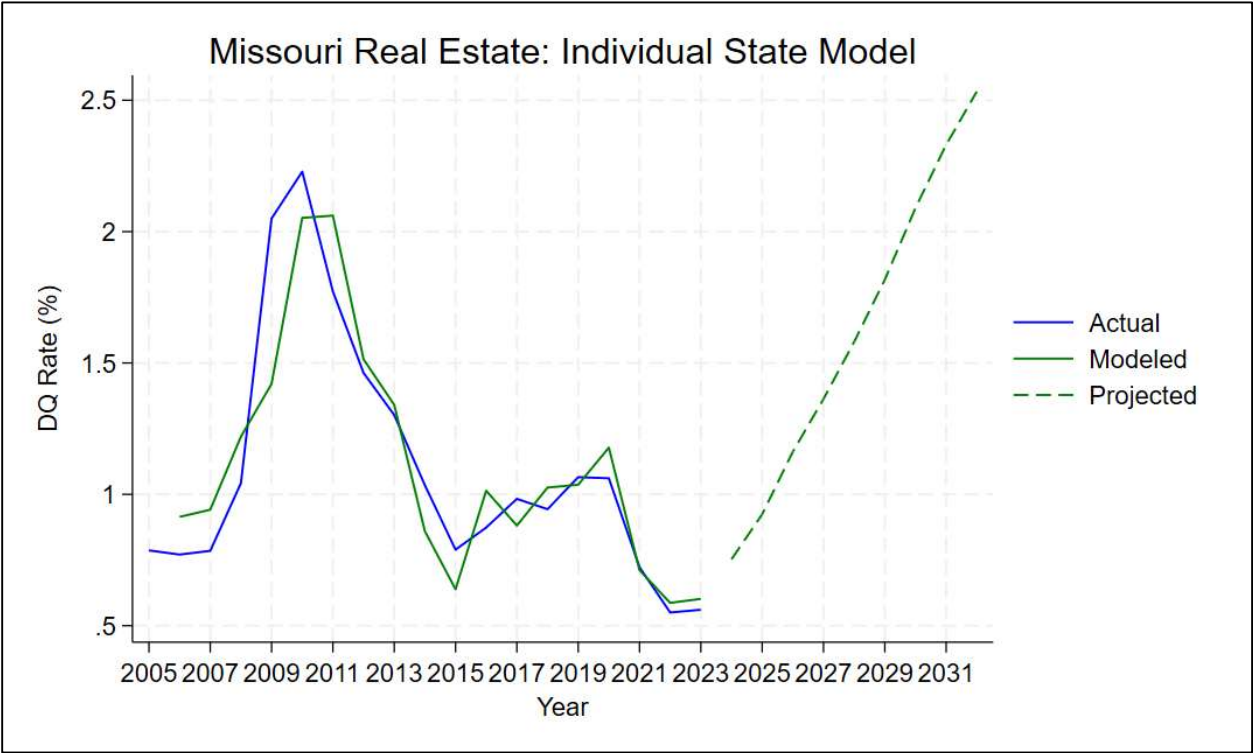


Figure 5.21: Nebraska Non-Real Estate Individual State Model Results Graph

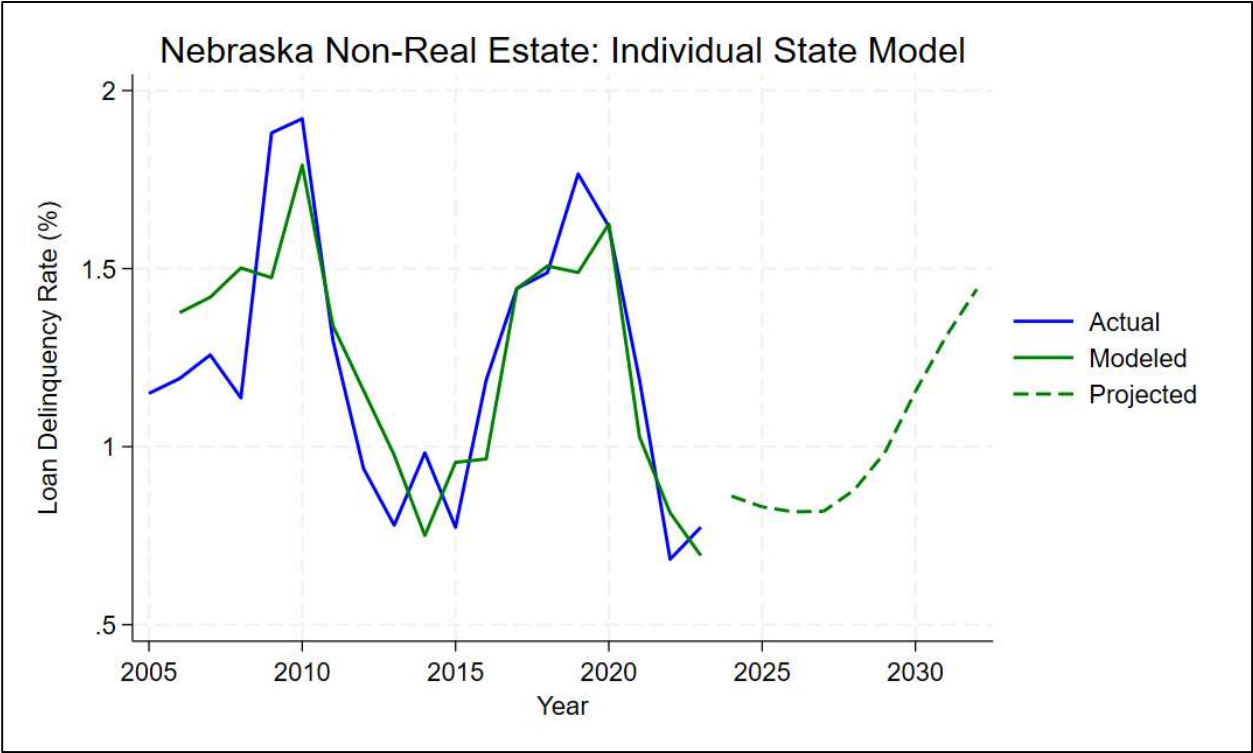


Figure 5.22: Nebraska Real Estate Individual State Model Results Graph

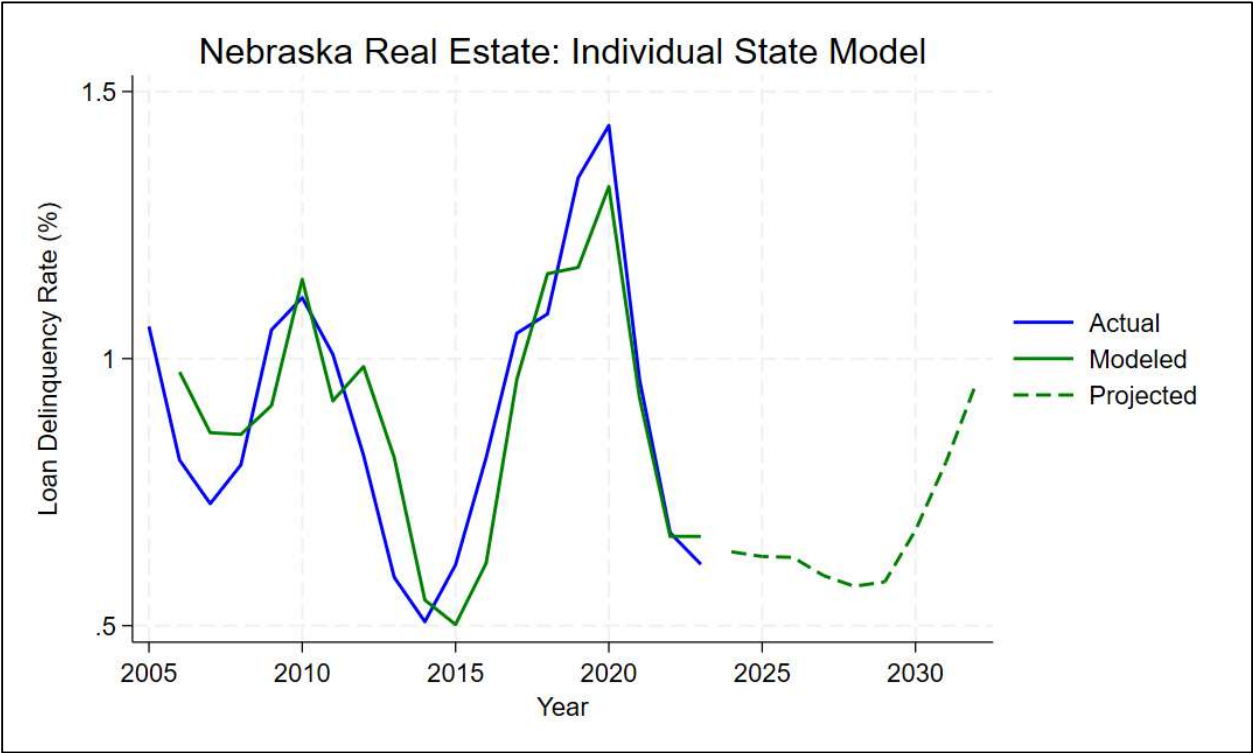


Figure 5.23: Arkansas Non-Real Estate Individual State Model Results Graph

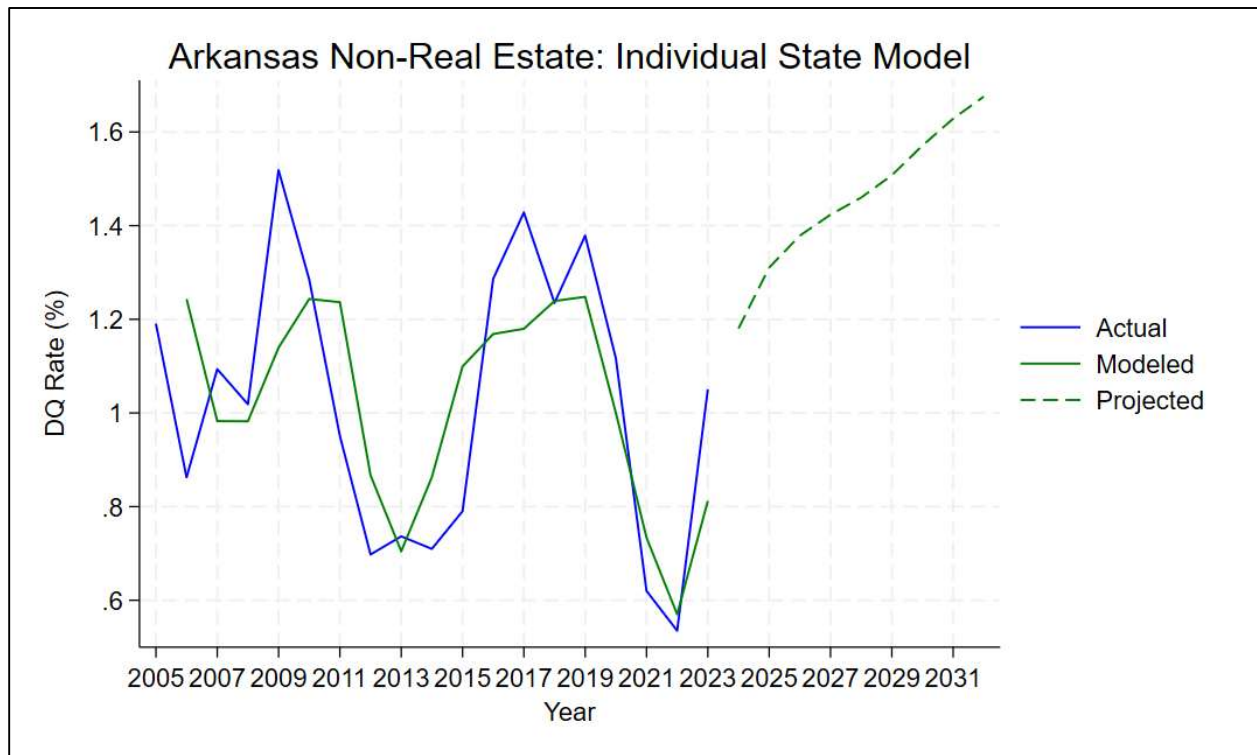


Figure 5.24: Arkansas Real Estate Individual State Model Results Graph

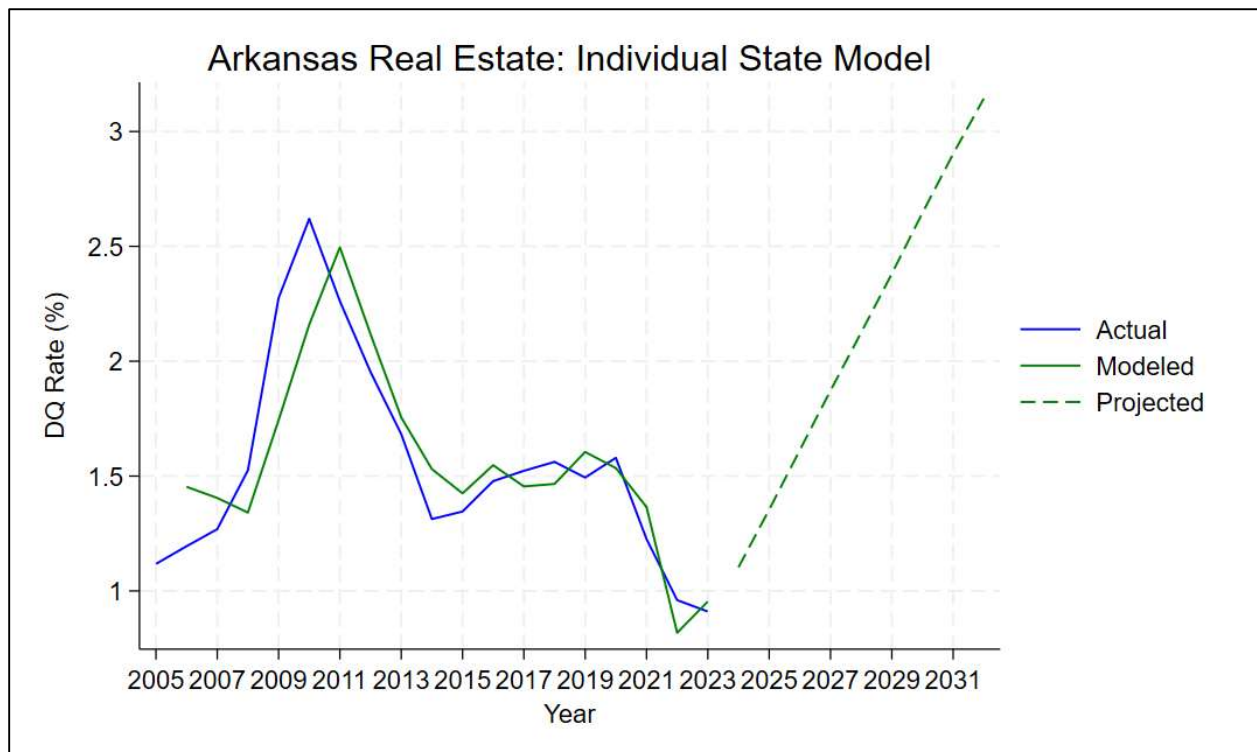


Figure 5.25: Illinois Non-Real Estate Individual State Model Results Graph

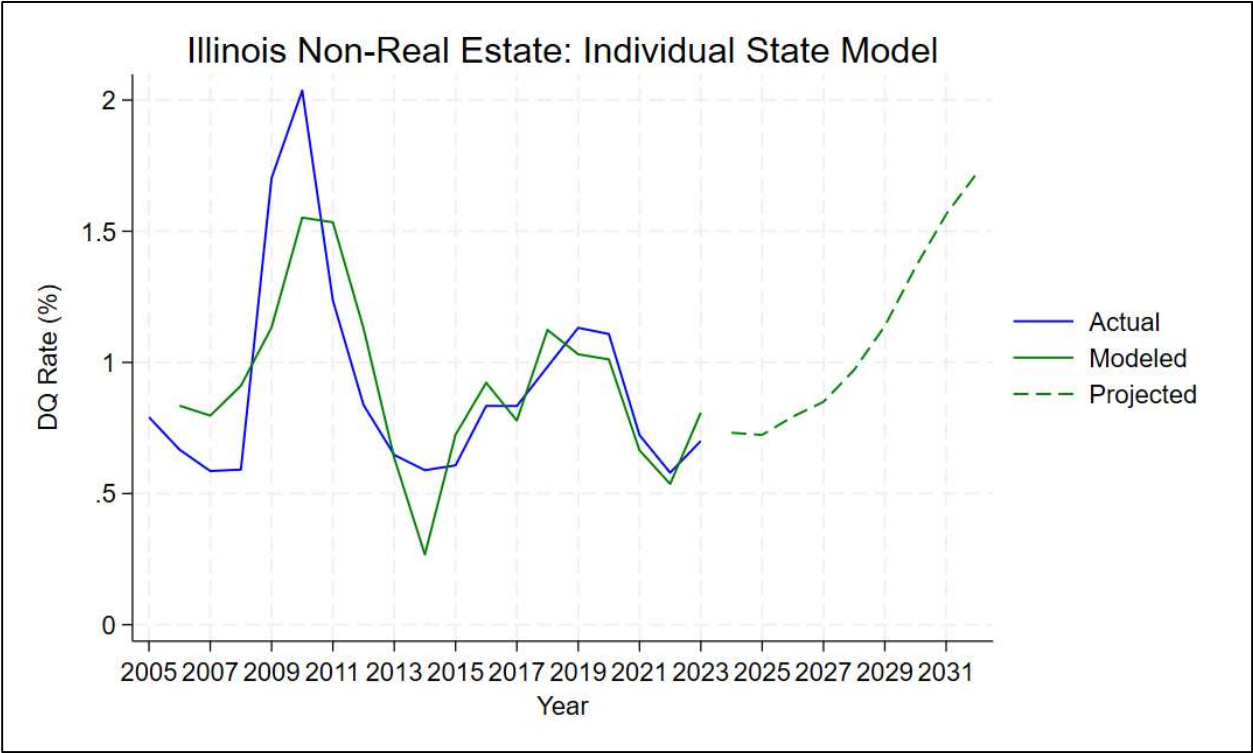


Figure 5.26: Illinois Real Estate Individual State Model Results Graph

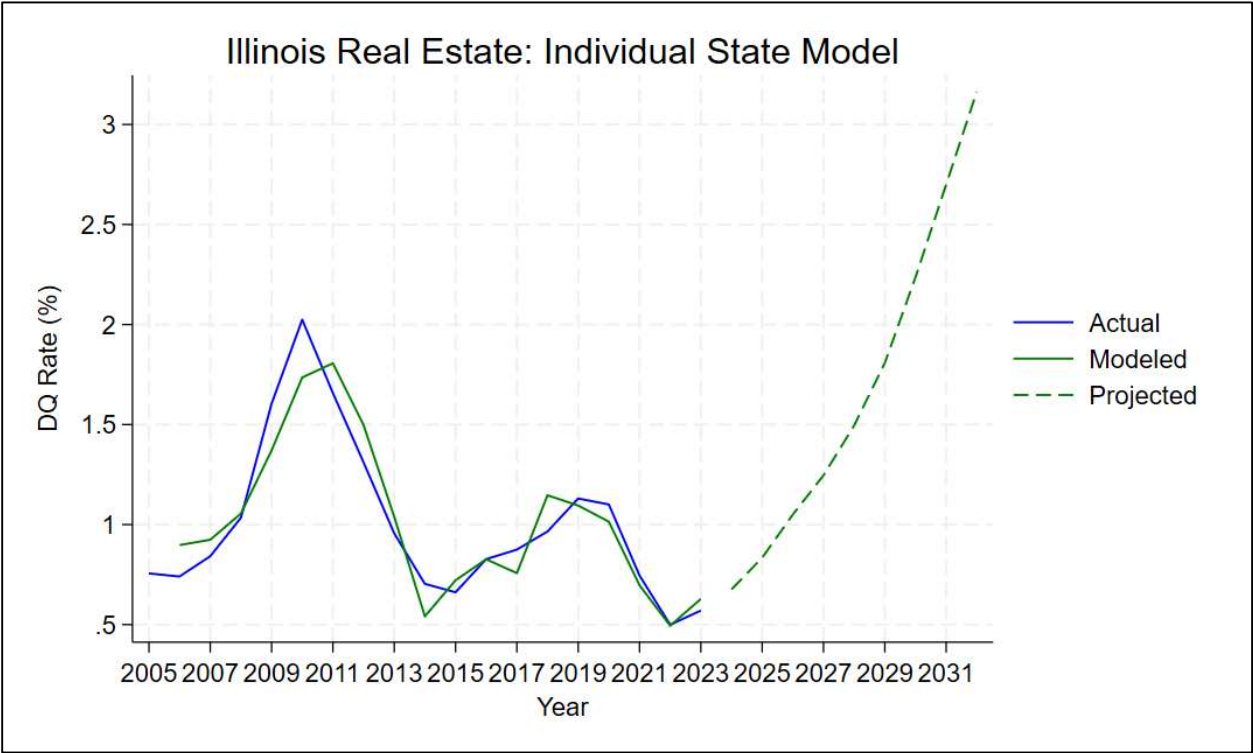


Figure 5.27: Minnesota Non-Real Estate Individual State Model Results Graph

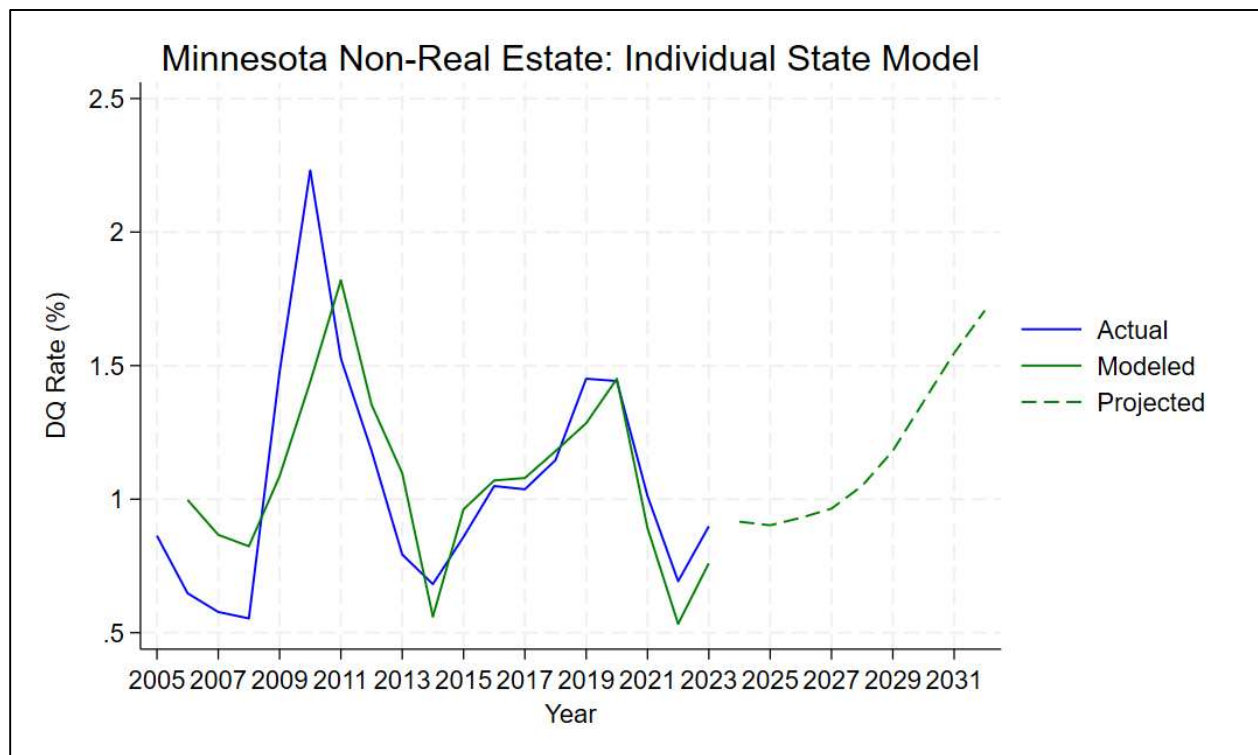
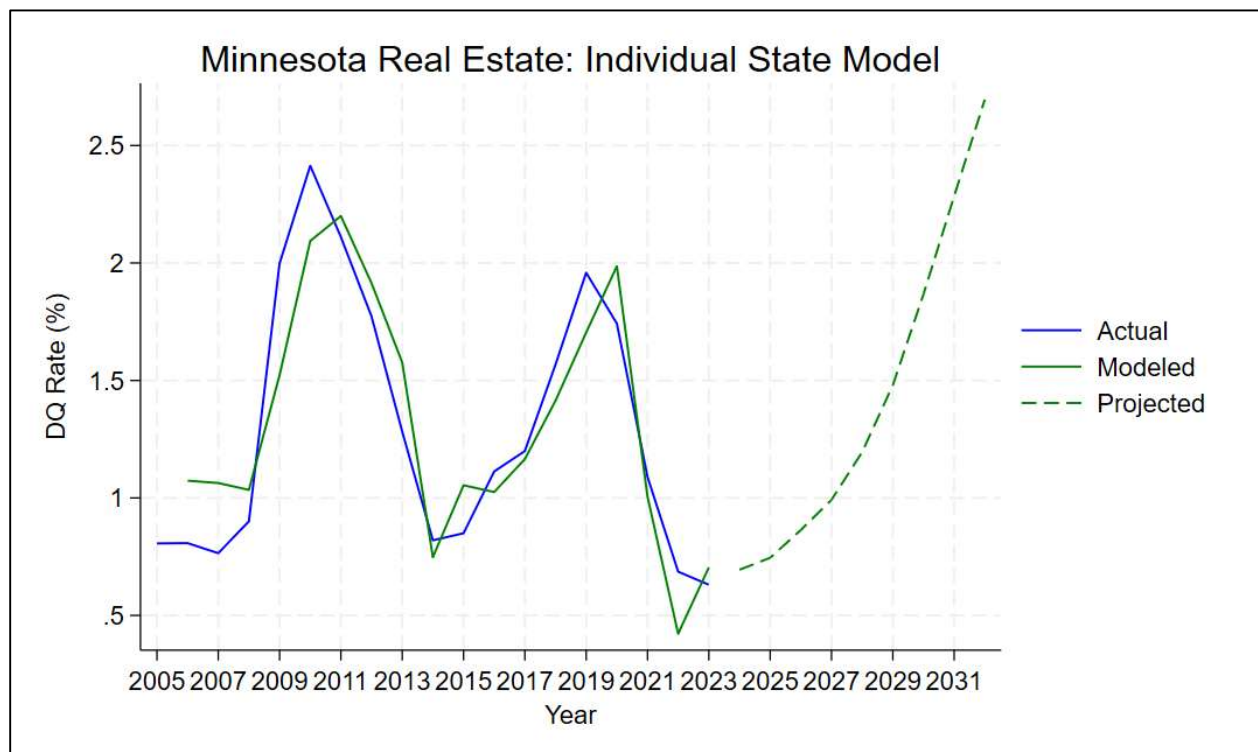


Figure 5.28: Minnesota Real Estate Individual State Model Results Graph



5.4 National Model Results:

The national model used national income and expenses for each state, while each state still used the delinquency rates for each of the non-real estate and real estate models. Results varied from expectations in several of the states and can be seen in **Table 5.4**. In Iowa, Kansas and Nebraska the results were as expected except for the total expenses coefficient in the Kansas real estate model. However, the national model did not yield results that made economic sense for Missouri, Arkansas, Illinois and Minnesota models, for two variables specifically: crop revenues and total expenses.

Table 5.5: National Model Results (Equations 5 & 6)

National Model Results								
Variable	Iowa Non- Real Estate	Iowa Real Estate	Kansas Non- Real Estate	Kansas Real Estate	Missouri Non- Real Estate	Missouri Real Estate	Nebraska Non-Real Estate	Nebraska Real Estate
Intercept	1.227	1.396	2.047	1.847	3.090	2.403	2.172	0.779
Crop Revenues	-0.005 (0.003)	-0.003 (0.002)	-0.002 (0.003)	-0.001 (0.002)	0.007 (0.007)	0.006* (0.003)	-0.003 (0.003)	-0.003 (0.002)
Livestock Revenues	-0.010** (0.004)	-0.005* (0.002)	-0.006 (0.004)	-0.004 (0.003)	-0.012 (0.007)	-0.008** (0.004)	-0.008* (0.004)	-0.004 (0.002)
Total Expenses	0.006* (0.003)	0.002 (0.002)	0.001 (0.004)	-0.008 (0.002)	-0.003 (0.008)	-0.003 (0.003)	0.003 (0.004)	0.002 (0.002)
Government Payment Revenues Lagged	-0.010 (0.006)	-0.011** (0.004)	-0.003 (0.007)	-0.016** (0.005)	-0.013 (0.013)	-0.015** (0.006)	-0.008 (0.007)	-0.013** (0.004)
Lagged Delinquency Rate	0.805*** (0.171)	0.964*** (0.146)	0.342 (0.281)	0.924*** (0.150)	0.246 (0.252)	0.613*** (0.137)	0.545* (0.199)	1.061*** (0.192)
RMSE	0.2139	0.1230	0.2498	0.1636	0.4416	0.2135	0.2419	0.1304
R ²	0.7907	0.8616	0.5883	0.8136	0.5629	0.8610	0.7229	0.8216
No. Observations	18	18	18	18	18	18	18	18

Table 5.6: National Model Results (Equations 5 & 6) Continued...

National Model Results						
Variable	Arkansas Non-Real Estate	Arkansas Real Estate	Illinois Non- Real Estate	Illinois Real Estate	Minnesota Non-Real Estate	Minnesota Real Estate
Intercept	2.593	2.645	2.625	2.707	2.357	3.559
Crop Revenues	-0.002 (0.002)	0.004 (0.002)	0.004 (0.004)	0.004 (0.003)	0.003 (0.004)	0.003 (0.004)
Livestock Revenues	-0.005 (0.003)	-0.007** (0.003)	-0.006 (0.005)	-0.005 (0.003)	-0.006 (0.005)	-0.007 (0.004)
Total Expenses	0.001 (0.003)	-0.003 (0.002)	-0.004 (0.005)	-0.004* (0.002)	-0.003 (0.005)	-0.004 (0.004)
Government Payment Revenues Lagged	-0.014** (0.005)	-0.014** (0.004)	-0.014 (0.008)	-0.015** (0.004)	-0.015 (0.009)	-0.023** (0.007)
Lagged Delinquency Rate	0.197 (0.209)	0.683*** (0.116)	0.417* (0.215)	0.632*** (0.129)	0.573** (0.221)	0.743*** (0.137)
RMSE	0.2014	0.1581	0.2989	0.1547	0.3325	0.2496
R^2	0.6764	0.9149	0.6213	0.8978	0.5800	0.8599
No. Observations	18	18	18	18	18	18

5.4.1 Non-Real Estate Delinquency Model

For the Iowa non-real estate national model, the overall model R^2 was 0.7907 and the RMSE was 0.2139. The R^2 in the non-real estate model for Iowa is lower than the R^2 in the individual state model and the RMSE for this model is higher than the individual state model as well. The Iowa non-real estate national model resulted in values that made economic sense, and three of the five variables were statistically significant. Coefficients are as follows: crop revenues -0.005, livestock revenues -0.010, total expenses 0.006, lagged government payments -0.010, and lagged delinquency rates 0.805. Of those variables total expenses were statistically significant at the 90% level, livestock revenues at the 95% level, and the lagged delinquency rate was statistically significant at the 99% level. A projected rise in delinquency rates from 2023 levels of just over 0.5% to nearly 2% by 2032 are shown in **Figure 5.29**.

The Kansas national model results for non-real estate were as expected and reported a stronger overall fit than the individual state level models comparatively with an overall model R^2 of 0.588 and the RMSE was 0.250. However, not a single variable was reported as statistically significant at even the 90% level. Coefficients are as follows: crop revenues -0.002, livestock revenues -0.006, total expenses 0.001, lagged government payments -0.003, and lagged delinquency rates 0.342. When comparing those values to the individual state level model the state level model had one value that was statistically significant, lagged delinquency rates, while the national model reported a higher R^2 and lower RMSE. **Figure 5.31** shows an upward trend in projected delinquency rates by increasing from around 0.8% in 2023 to just under 1.5% by 2032.

The national model for Missouri non-real estate delinquencies returned an R^2 of 0.563 which is higher than the individual state model, while also returning the highest RMSE of the national models at 0.442 but still lower than the individual state model RMSE. The national

model for Missouri non-real estate delinquency rates resulted in no statistically significant values and two coefficients that were not as expected: crop revenues of 0.007 and total expenses of -0.003. Variables that reported coefficients as expected: livestock revenues -0.012, lagged government payments -0.013, and lagged delinquency rate 0.246. **Figure 5.33** shows projected delinquency rates for Missouri with a projected increase from just under 0.5% in 2023 to just over 1% by 2032.

Nebraska national model results showed an R^2 of 0.723 which is higher than the individual state model and the RMSE of 0.242 is lower than the individual state model. The non-real estate model coefficients were as expected with only two variables being statistically significant. Coefficients are as follows: crop revenues -0.003, livestock revenues -0.008, total expenses 0.003, lagged government payments -0.008, and lagged delinquency rates 0.545. Only livestock revenues and lagged delinquency rates were statistically significant both at the 90% level. The projected delinquency rates for Nebraska's non-real estate model show an uptick in delinquencies from around 0.75% in 2023 to just under 2% by 2032 shown in **Figure 5.35**.

The Arkansas non-real estate model R^2 is 0.676 which is higher than the individual state level model. RMSE is reported at 0.201 which is lower than the individual state level model. The coefficient results did not deviate from expectations but only one variable was statistically significant: lagged government payments at the 95% level. Coefficient results are as follows: crop revenues -0.002, livestock revenues -0.005, total expenses 0.001, lagged government payments -0.014, and lagged delinquency rates of 0.197. **Figure 5.37** shows projected increases in delinquency rates for Arkansas' non-real estate loans from just over 1% in 2023 to over 1.5% by 2032.

The overall model R^2 for the Illinois non-real estate model was 0.621, which was higher than the state level model. Meanwhile, the RMSE of 0.299 was slightly lower than the state level model. For the Illinois non-real estate national model only one variable was statistically significant, and two variables deviated from expectations. Crop revenues 0.004 and total expenses -0.004 - both reported values opposite of what was expected, and neither were statistically significant. The rest of the coefficient signs were as expected and are as follows: livestock revenues -0.006, lagged government payments -0.014, and lagged delinquency rates 0.417. The only statistically significant variable was the lagged delinquency rate at the 90% level. Illinois projected delinquency rates in **Figure 5.39** show a rise in projected delinquency rates from around 0.7% in 2023 to nearly 1.5% by 2032.

Minnesota's non-real estate national model results followed a similar trend to Arkansas and Illinois in that both crop revenues and total expenses reported signs that did not follow economic theory. The overall model R^2 is 0.580 and the RMSE is 0.333. Coefficient's for crop revenues is 0.003 and for total expenses it is -0.003, and neither is statistically significant. The rest of the model coefficients are as follows: livestock revenues -0.006, lagged government payments -0.015, and lagged delinquency rate 0.573. Only the lagged delinquency rate was statistically significant at the 95% level. **Figure 5.41** shows projected increases in delinquency rates from just under 1% in the delinquency rate in 2023 to around 1.7% by 2032.

5.4.2 Real Estate Delinquency Model

The R^2 was 0.8616 and the RMSE was 0.1230 for the Iowa real estate model, which was the smallest RMSE of any of the models in this study. Both the R^2 and RMSE reported better values than the individual state models. The model also resulted in three statistically significant variables. Coefficients are as follows: crop revenues -0.003, livestock revenues -0.005, total

expenses 0.002, lagged government payments -0.011, and the lagged delinquency rate 0.964. Livestock revenues were statistically significant at the 90% level, lagged government payments were statistically significant at the 95% level and the lagged delinquency rate was statistically significant at the 99% level. **Figure 5.30** shows an increase in delinquency rates from 0.5% in 2023 to just under 2.5% by 2032.

The overall model fit for the Kansas real estate model gave an R^2 of 0.814 which was much higher than the individual state model and the national model also reported a lower RMSE of 0.164. Two of the variables were statistically significant, however the total expenses coefficient did not result in a value that was expected at -0.008, although it was not statistically significant. Coefficients for the rest of the variables are as follows: crop revenues -0.001, livestock revenues -0.004, lagged government payments -0.016, and lagged delinquency rates 0.924. Lagged government payments were statistically significant at the 95% level and the lagged delinquency rate was statistically significant at the 99% level. The projected values for Kansas in **Figure 5.32** show an uptrend in loan delinquency rates from around 0.8% to just under 3% by 2032.

For the Missouri real estate model an overall model R^2 at 0.861 was reported and is higher than the state level model. The national model also reported a lower RMSE at 0.214. For the reported coefficients, both crop revenues 0.006 and total expenses -0.003 did not give coefficients as expected and reported that crop revenues was statistically significant at the 90% level. Livestock revenues -0.008 was statistically significant at the 95% level, lagged government payments -0.015 also statistically significant at the 95% level, and lagged delinquency rates 0.613 was statistically significant at the 99% level. In **Figure 5.34**

delinquencies are projected to increase from around 2023 values of 0.5% to just over 1.5% by 2032.

The Nebraska real estate model reported an overall R^2 of 0.823 and an RMSE of 0.130, both of which were a better statistical fit than the individual state model. Results for the coefficients were similar to the non-real estate model in that they did not report values that were unexpected and reported two variables that were statistically significant: lagged government payments at the 95% level and the lagged delinquency rate at the 99% level. Coefficients for model variables are as follows: crop revenues -0.003, livestock revenues -0.004, total expenses 0.002, lagged government payments -0.013, and lagged delinquency rates 1.061. The projected delinquency rates in **Figure 5.36** show a sharp increase in delinquency rates from 2023 values of 0.6% to just under 2.5% by 2032.

Arkansas' national model R^2 0.676 and the RMSE is 0.201. The real estate model for Arkansas at the national level reported two values that strayed from expectations: crop revenues 0.004 and total expenses -0.003, neither were statistically significant. The other variable coefficients are as follows: livestock revenues -0.007, lagged government payments -0.014, and lagged delinquency rates at 0.683. All three were statistically significant with both livestock revenues and lagged government payments being significant at the 95% level while the lagged delinquency rate was statistically significant at the 99% level. **Figure 5.38** shows Arkansas delinquency rates increasing from around 1% in 2023 to around 2.3% by 2032.

The overall R^2 for the Illinois real estate model is 0.898, indicating large explanatory power while the RMSE was on the lower end of models at 0.155. The Illinois real estate national model had similar issues to the non-real estate model with coefficient signs as both the crop revenues coefficient of 0.004 and total expense coefficient of -0.004 reported signs opposite of

the expectation. The total expense variable is statistically significant at the 90% level. The other variable coefficients are as follows: livestock revenues -0.005, lagged government payments -0.015, and lagged delinquency rate 0.632. Lagged government payments was significant at the 95% level and the lagged delinquency rate was significant at the 99% level. **Figure 5.40** shows an increase in projected delinquency rates for Illinois from just over 0.5% to around 1.8% by 2032.

For the real estate national model results for Minnesota the overall model R^2 is 0.840 and RMSE is 0.250 both indicating better fit than the individual state model. Results showed crop revenues and total expenses deviating from expectations, with coefficients of 0.003 and -0.004 respectively. Neither variable was statistically significant. The rest of the coefficients are as follows: livestock revenues -0.007, lagged government payments -0.023, and lagged delinquency rates of 0.743. The lagged government payments were significant at the 95% level and lagged delinquency rate was significant at the 99% level. Lastly, **Figure 5.42** shows a rise in delinquency rates from just over 0.5% in 2023 to just under 3% by 2032.

Figure 5.29: Iowa Non-Real Estate National Model Results Graph

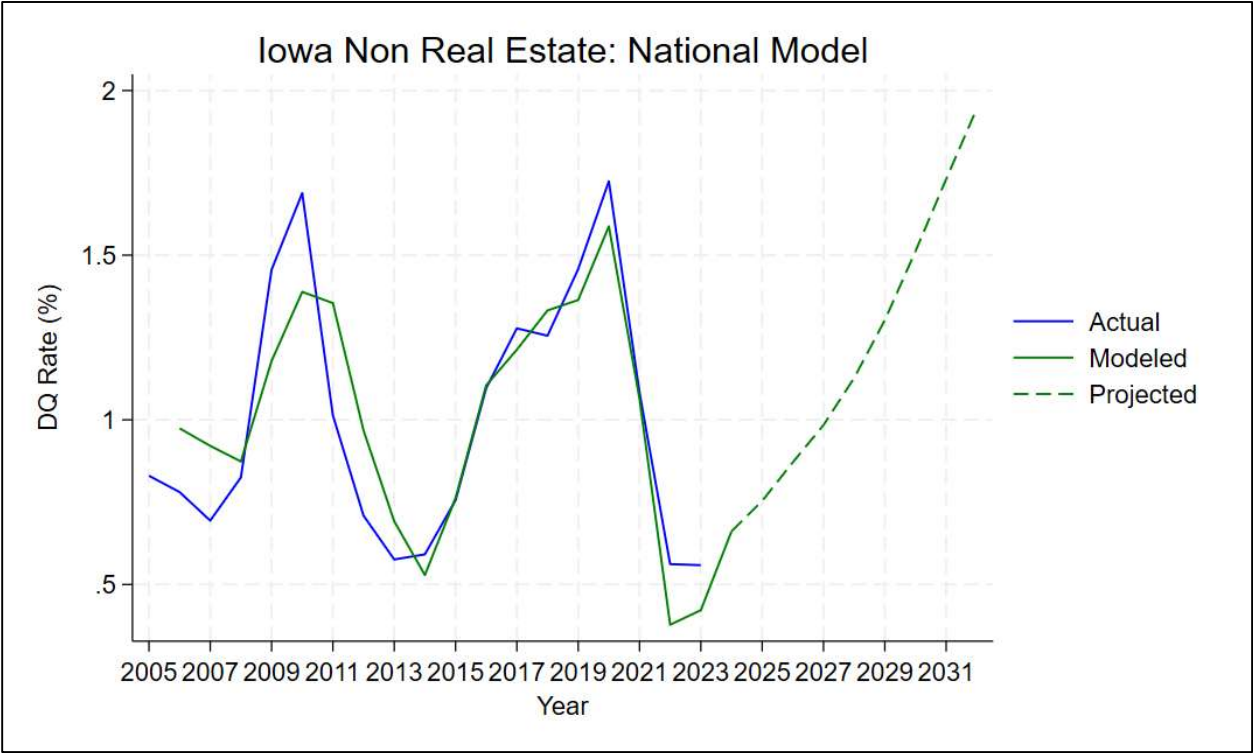


Figure 5.30: Iowa Real Estate National Model Results Graph

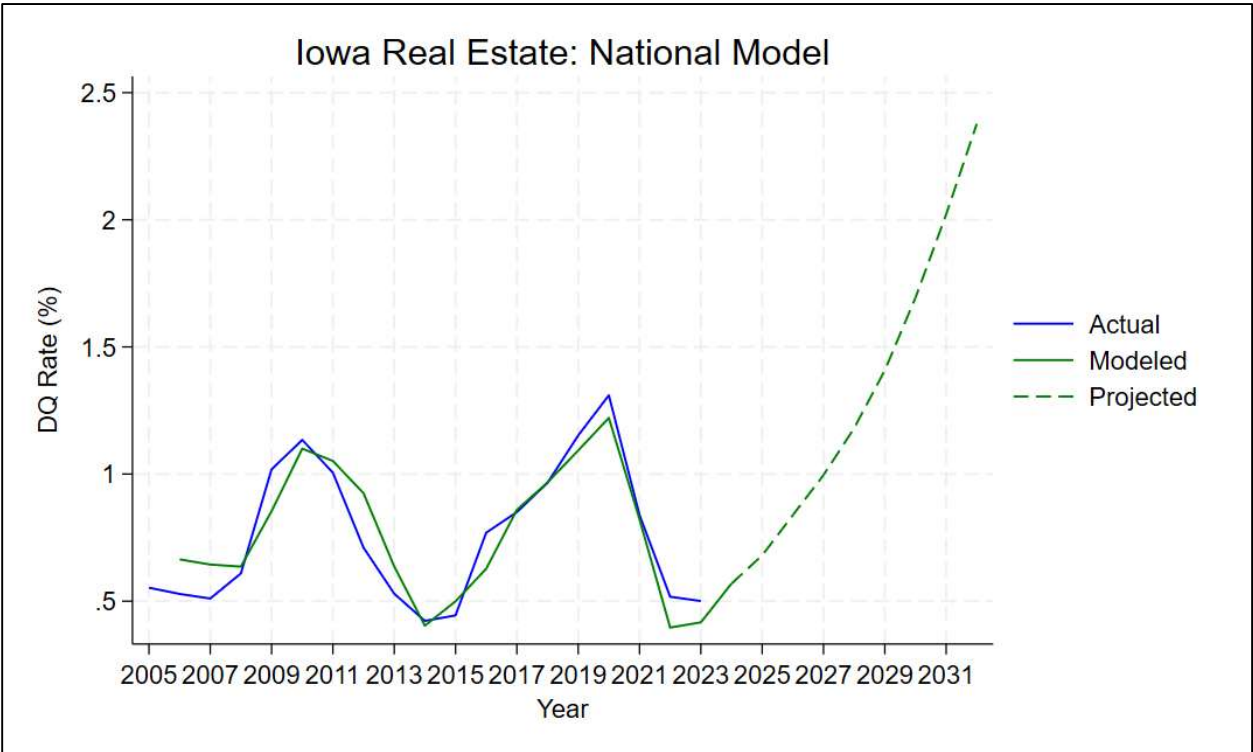


Figure 5.31: Kansas Non-Real Estate National Model Results Graph

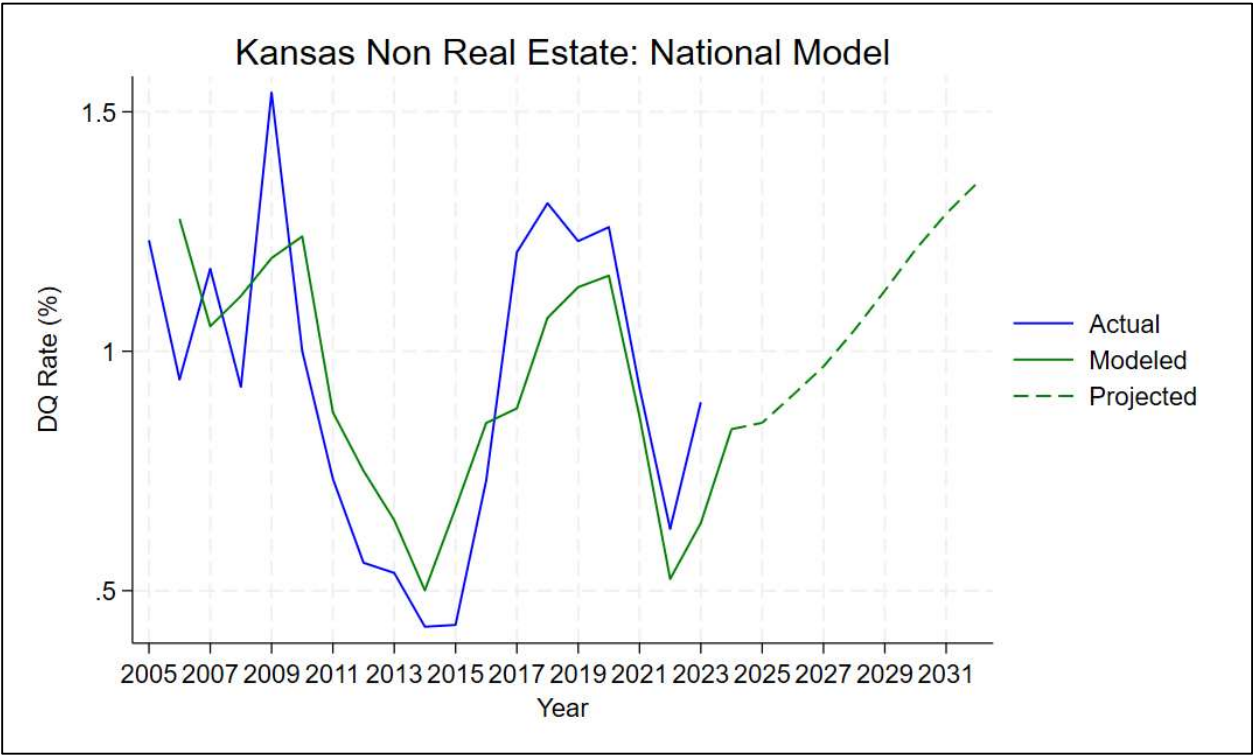


Figure 5.32: Kansas Real Estate National Model Results Graph

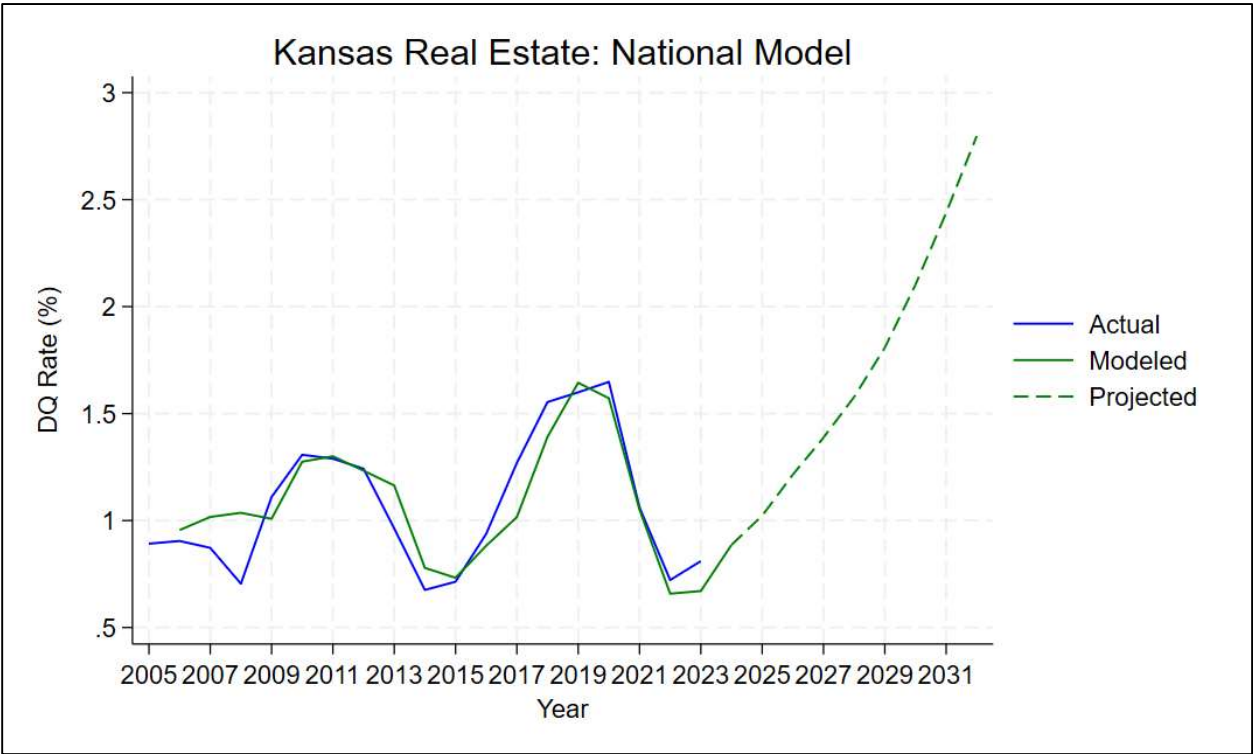


Figure 5.33: Missouri Non-Real Estate National Model Results Graph

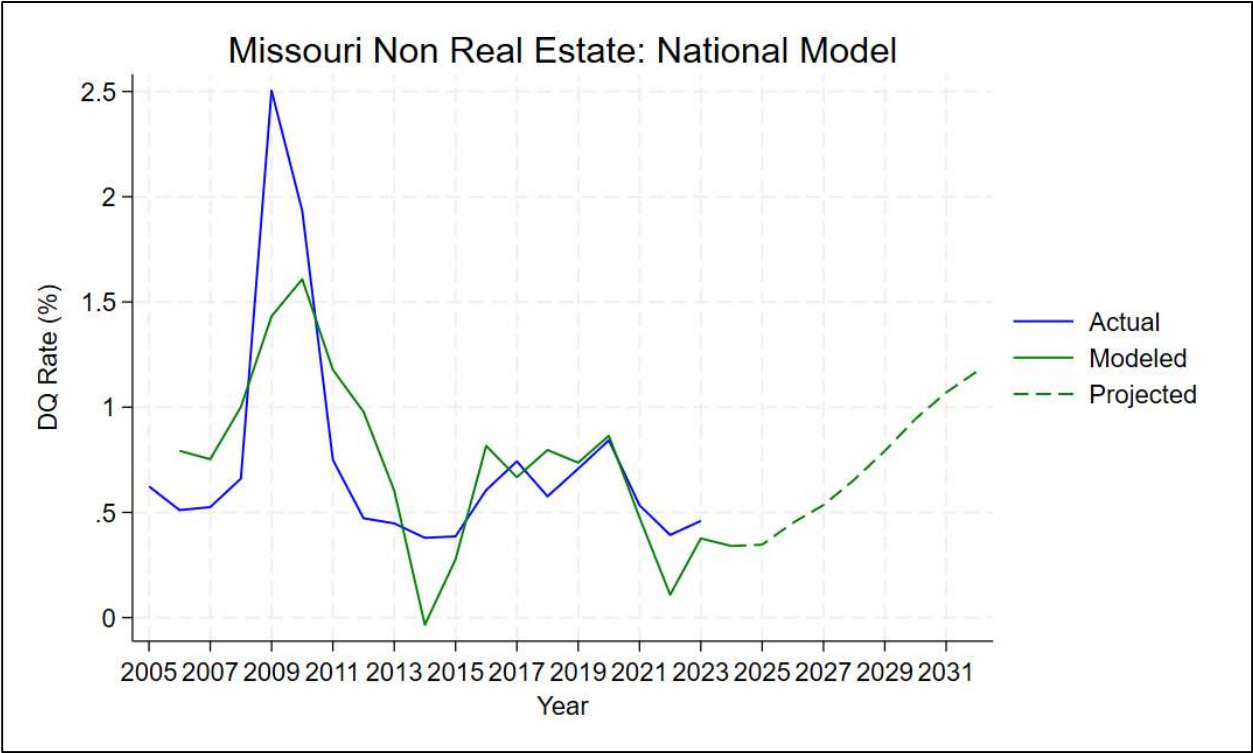


Figure 5.34: Missouri Real Estate National Model Results Graph

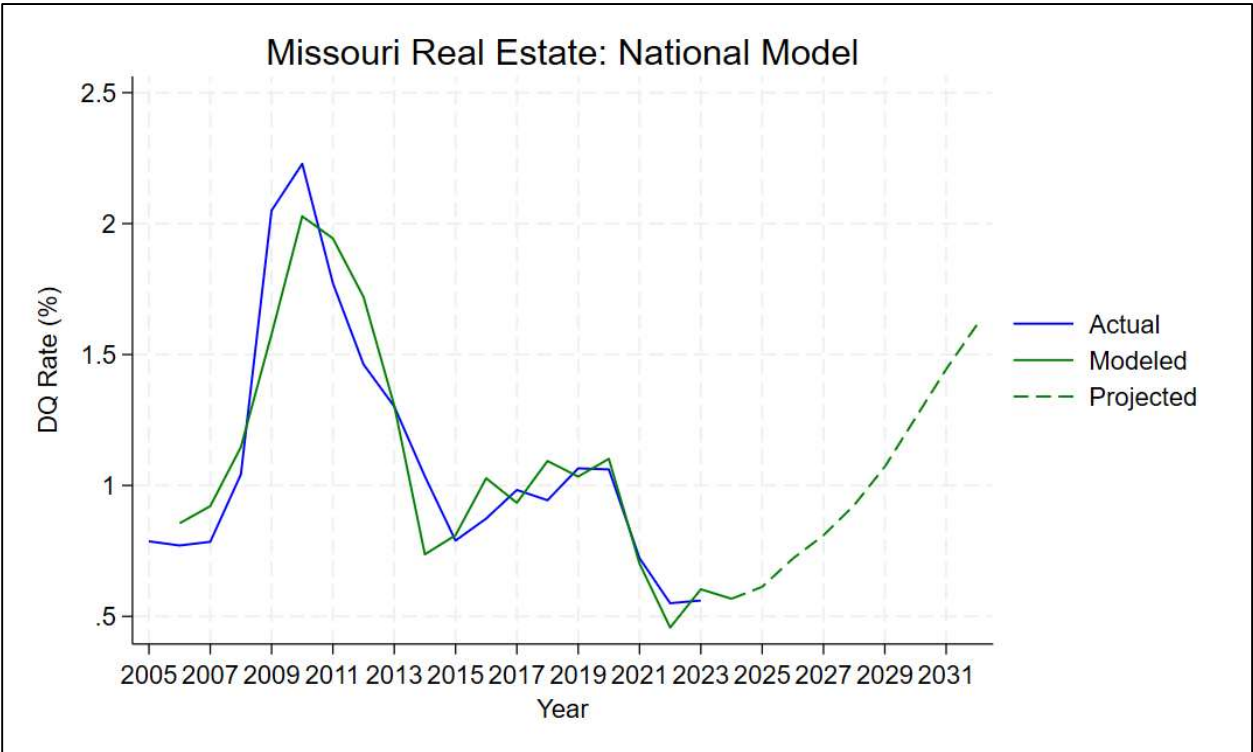


Figure 5.35: Nebraska Non-Real Estate National Model Results Graph

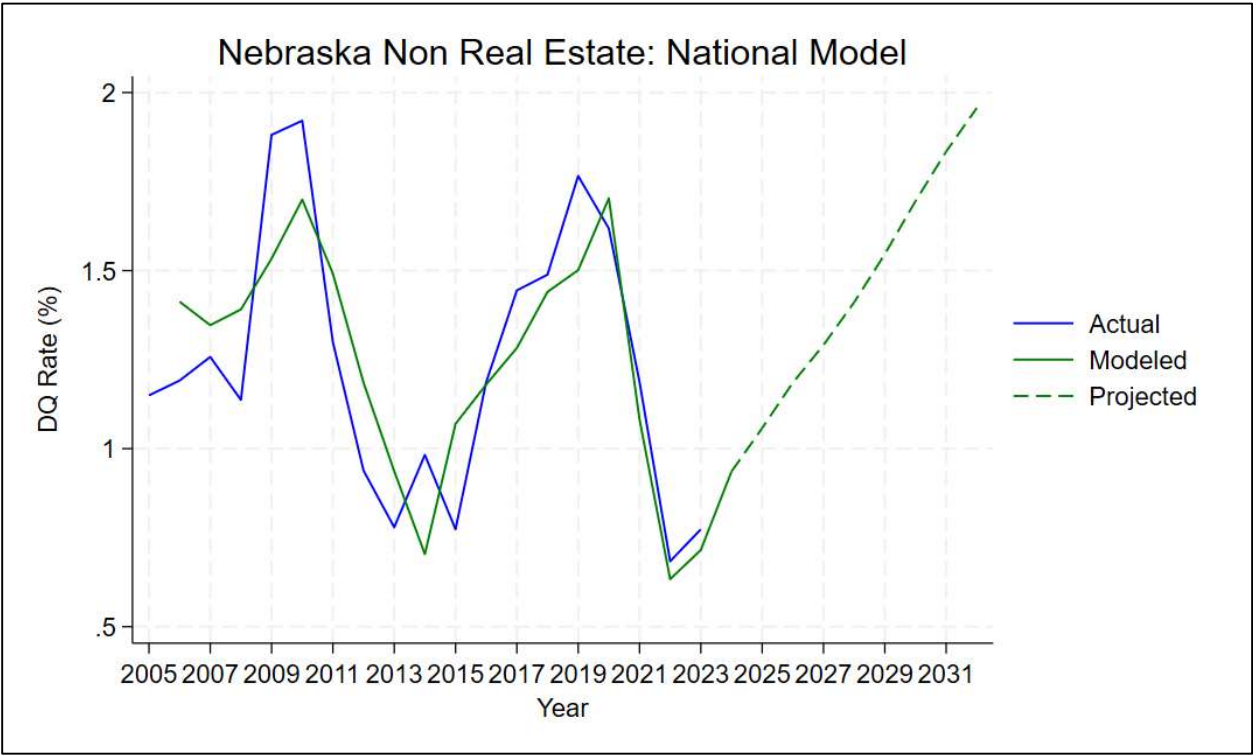


Figure 5.36: Nebraska Real Estate National Model Results Graph

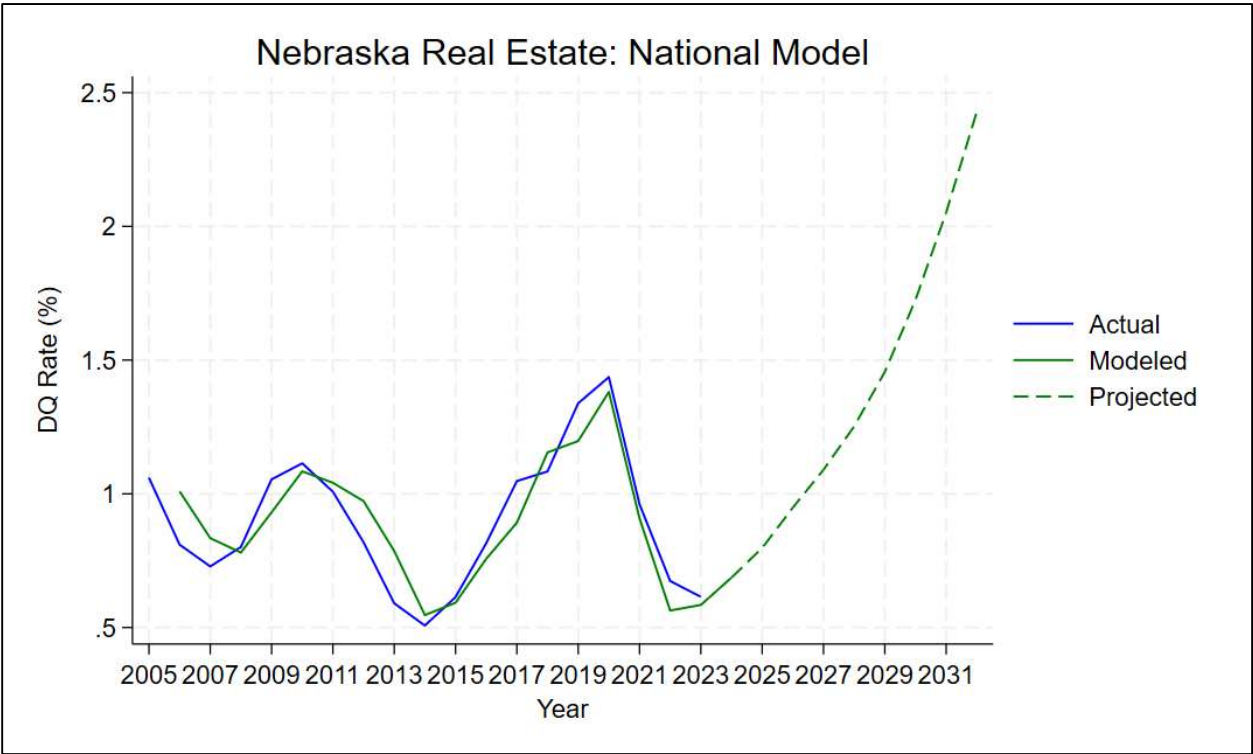


Figure 5.37: Arkansas Non-Real Estate National Model Results Graph

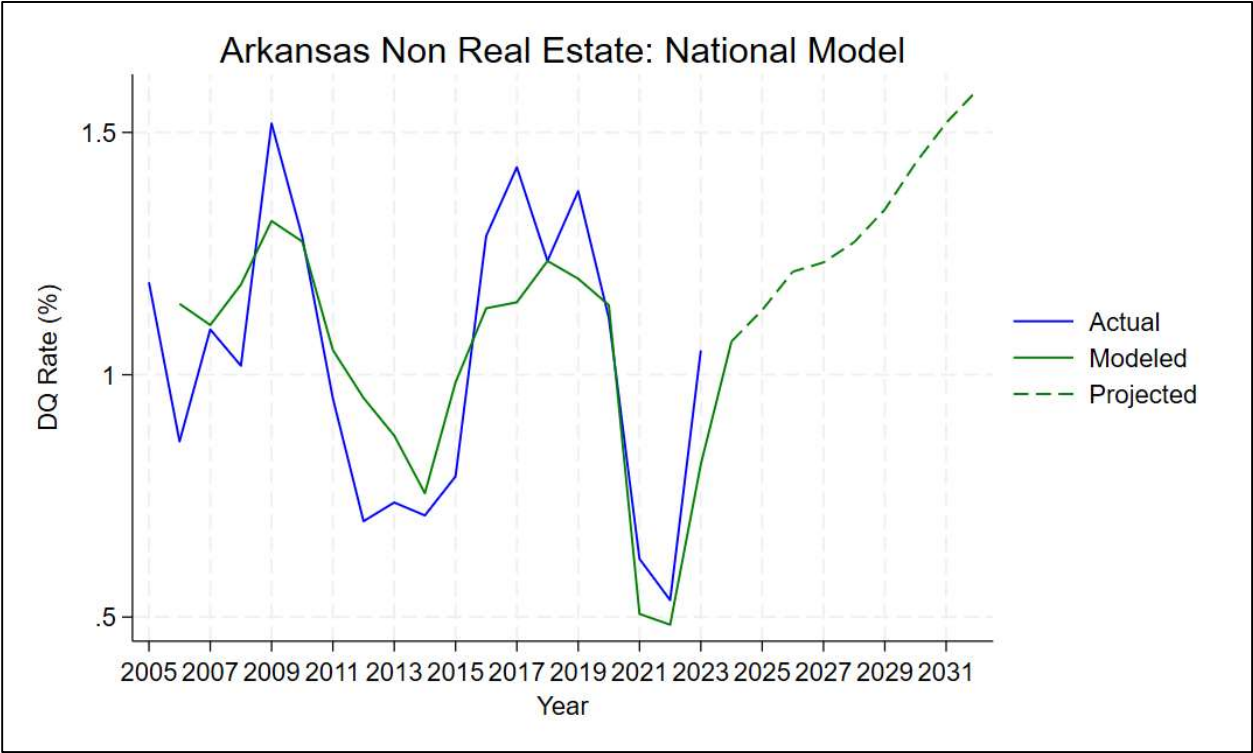


Figure 5.38: Arkansas Real Estate National Model Results Graph

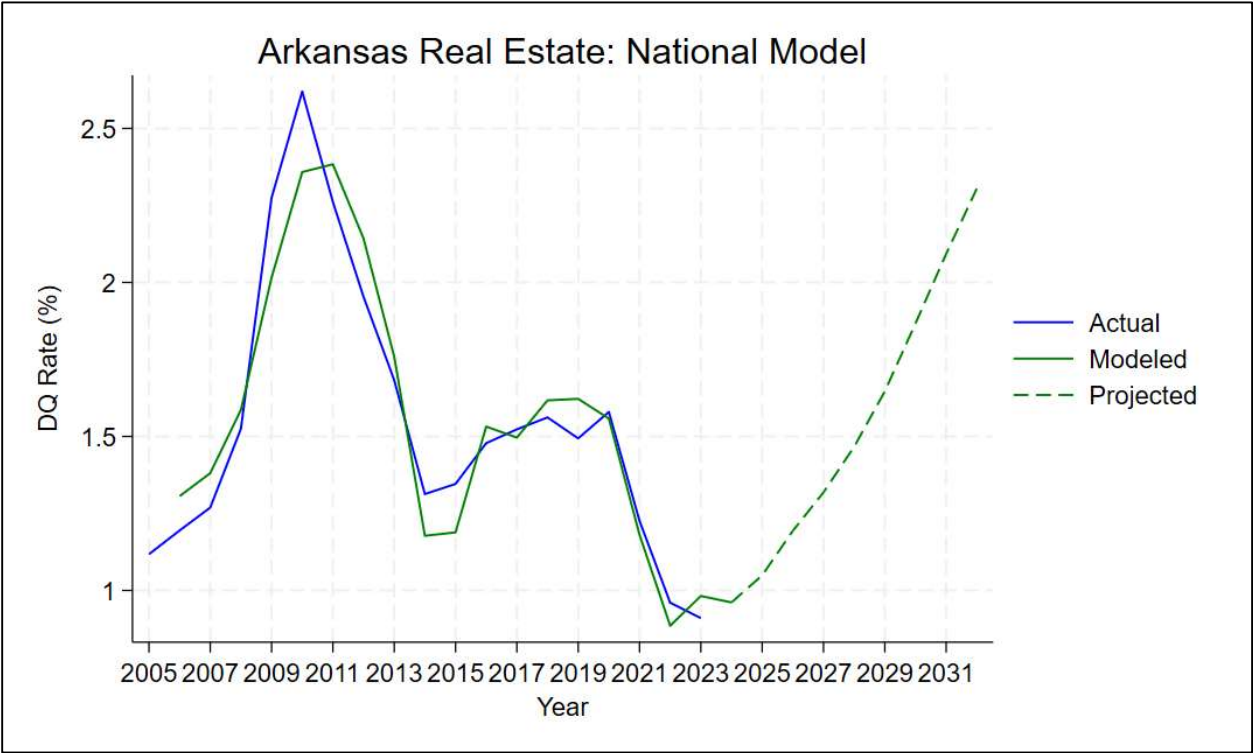


Figure 5.39: Illinois Non-Real Estate National Model Results Graph

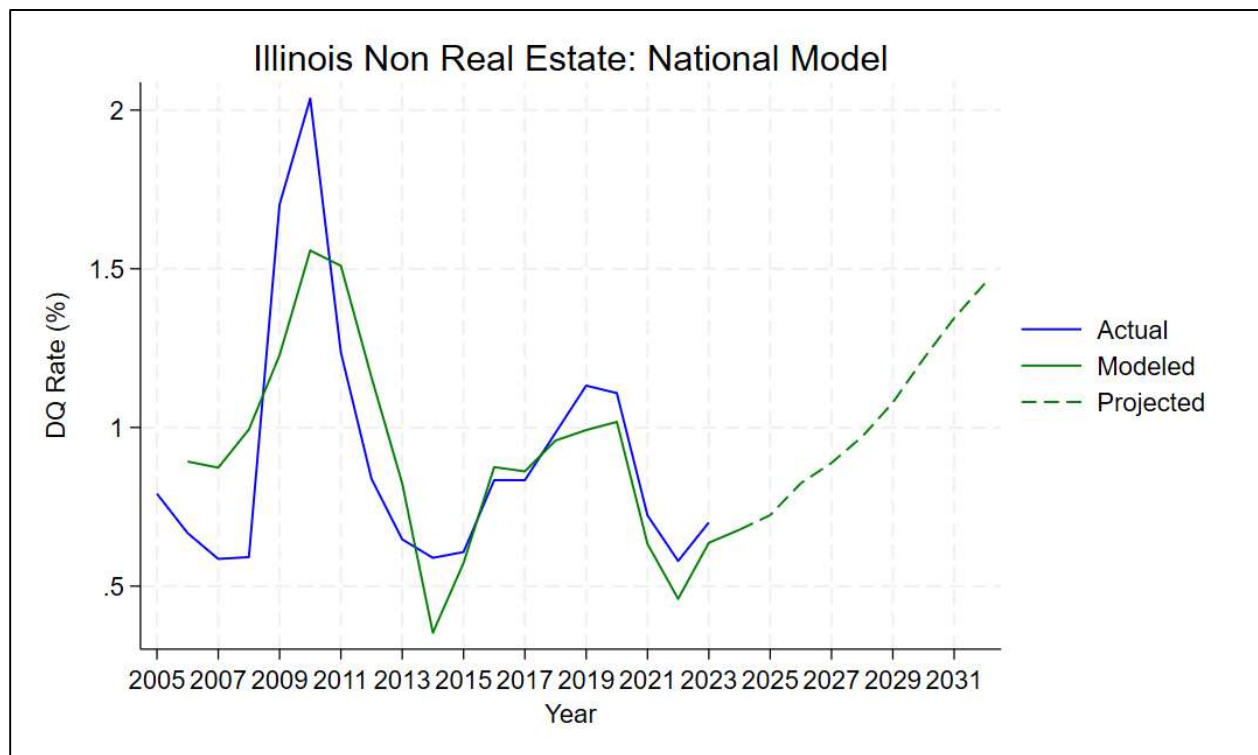


Figure 5.40: Illinois Real Estate National Model Results Graph

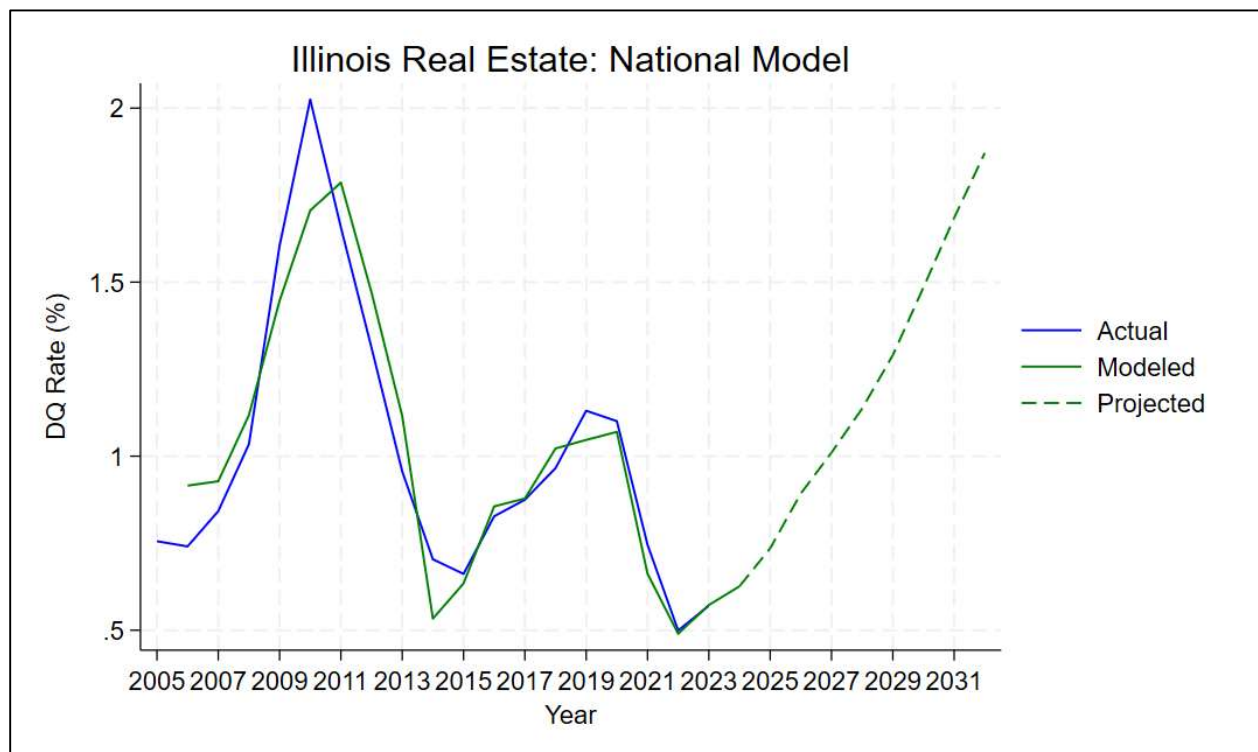


Figure 5.41: Minnesota Non-Real Estate National Model Results Graph

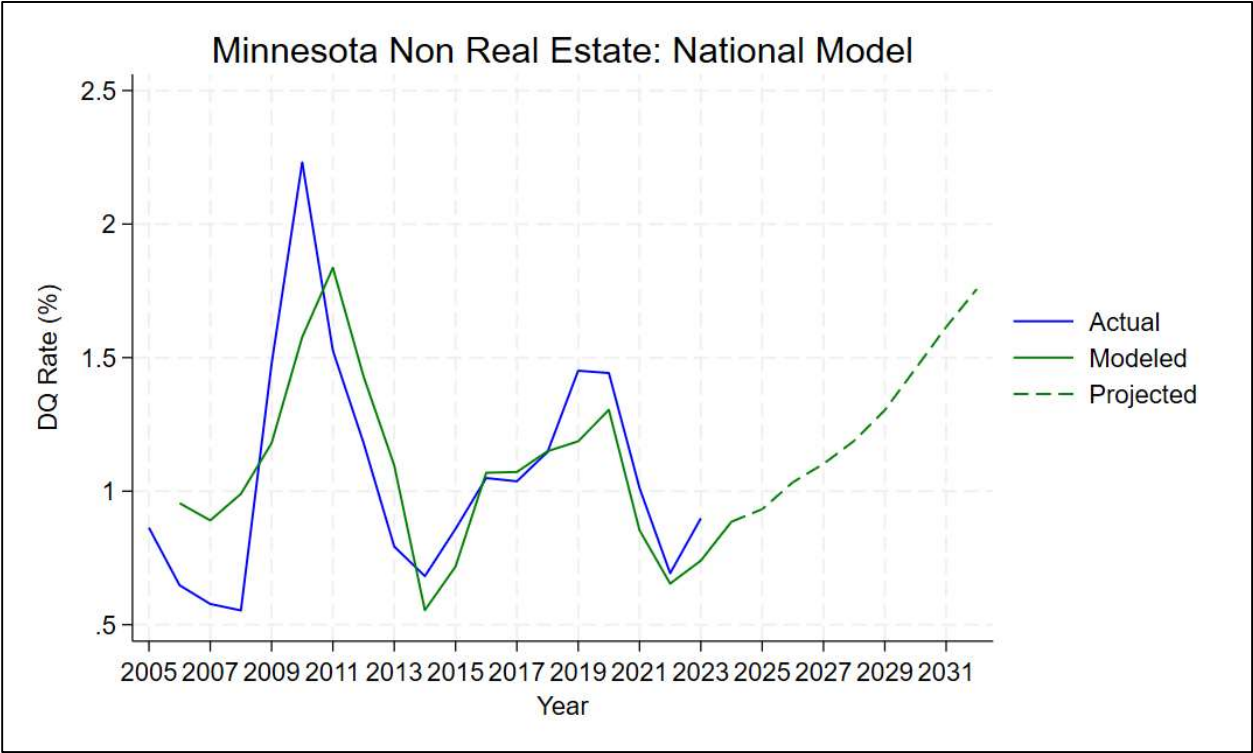
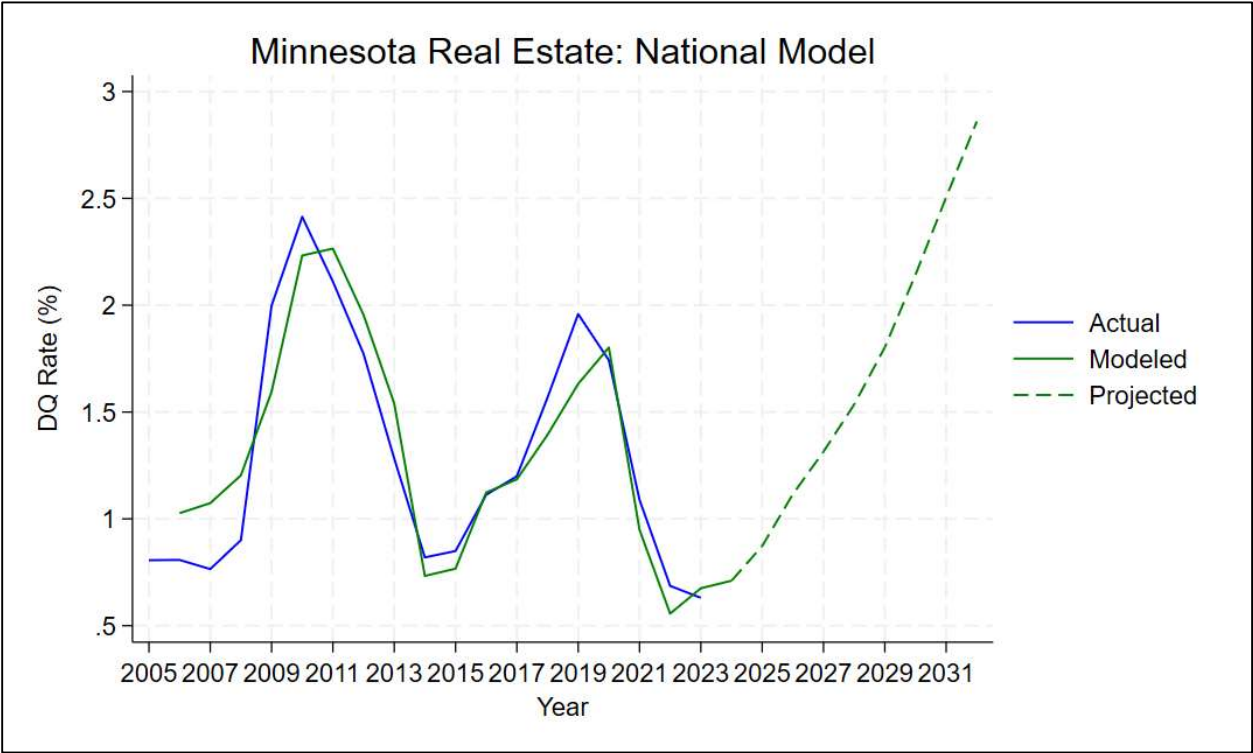


Figure 5.42: Minnesota Real Estate National Model Results Graph



5.5 Model Comparison:

The models yielded broadly similar statistical performance, yet the coefficient estimates differ in aligning with economic expectation between models. Although the national models achieved a slightly better overall statistical fit, evidenced by a marginally lower average RMSE and a slightly higher R^2 , some coefficients for Kansas, Missouri, Arkansas, Illinois, and Minnesota often deviated from economic theory and yielded opposite signs from expected. Specifically, the crop revenues variable for both models in Missouri, both models in Illinois, both models for Minnesota, and the real estate model for Arkansas yielded an opposite sign from expectations. In the real estate national model for Missouri the crop revenues variable was also statistically significant while deviating from expectations. For the total expense variable both models in Missouri, both models in Illinois, both models in Minnesota, the Kansas real estate model, and the Arkansas real estate model yielded coefficient results that were not as expected. The total expense variable for Illinois real estate was also statistically significant.

In contrast, the individual state-level models produced a few less anomalies. For crop revenues both Missouri models and the Illinois models produced results that were opposite of the expected sign. For the total expense variable, both Missouri models, both Illinois models, and the Arkansas real estate model were the opposite of what was expected as well. This divergence highlights the inherent trade-off between statistical fit and models that conform with economic theory. In **Table 5.6** below, the table shows R^2 , RMSE, number of statistically significant variables, and number of variables that make economic sense in each model to help understand which models make the most sense. None of the variables in the state level models that resulted in signs that were unexpected were statistically significant.

In total there was one more statistically significant variable in the individual state level models than in the national level models, however there were six variables that made more economic sense in the individual state level model than in the national level model. Meanwhile the R^2 on average was 0.6 points higher in the national level models and about 0.3 points lower in the average RMSE.

The pooled panel model presented a high statistical fit with the highest R^2 of all the models while also exhibiting a relatively reasonable RMSE. For the non-real estate pooled model every variable was statistically significant at the 95% level except for total expenses with all signs making economic sense. The real estate model returned coefficients that were all statistically significant at the 95% level except for total expenses and livestock revenues, while total expenses exhibited the opposite sign from prior expectations.

Table 5.7: Model Comparison Table

Model Type	R ²	RMSE	Number of Significant Variables (excluding binary variables)	Number of variables that make economic sense
Non-Real Estate Models				
Panel Model Results				
State Level Non-Real Estate Panel Model	0.9256	0.3075	4	5
Individual State Level Non-Real Estate Model				
Iowa Non-Real Estate	0.7991	0.2096	5	5
Kansas Non-Real Estate	0.4914	0.2777	0	5
Missouri Non-Real Estate	0.4900	0.4770	0	3
Nebraska Non-Real Estate	0.7131	0.2461	3	5
Arkansas Non-Real Estate	0.5271	0.2435	0	5
Illinois Non-Real Estate	0.6143	0.3016	1	3
Minnesota Non-Real Estate	0.5627	0.3393	1	5
National Level Non-Real Estate Models				
Iowa Non-Real Estate	0.7907	0.2139	3	5
Kansas Non-Real Estate	0.5883	0.2498	0	5
Missouri Non-Real Estate	0.5629	0.4416	0	3
Nebraska Non-Real Estate	0.7229	0.2419	2	5
Arkansas Non-Real Estate	0.6764	0.2014	1	5
Illinois Non-Real Estate	0.6213	0.2989	1	3
Minnesota Non-Real Estate	0.5800	0.3325	1	3
Real Estate Models				
Panel Model				
State Level Real-Estate Panel Model	0.9662	0.2321	3	4
Individual State Level Real Estate Model				
Iowa Real Estate	0.8113	0.1436	3	5
Kansas Real Estate	0.6693	0.2179	2	5
Missouri Real Estate	0.8226	0.2412	3	3
Nebraska Real Estate	0.7671	0.1490	4	5
Arkansas Real Estate	0.7649	0.2629	1	4
Illinois Real Estate	0.8845	0.1645	2	3
Minnesota Real Estate	0.8302	0.2749	3	5
National Level Real Estate Models				
Iowa Real Estate	0.8616	0.1230	3	5
Kansas Real Estate	0.8136	0.1636	2	4
Missouri Real Estate	0.861	0.2135	4	3
Nebraska Real Estate	0.8216	0.1304	2	5
Arkansas Real Estate	0.9149	0.1581	3	3
Illinois Real Estate	0.8978	0.1547	3	3
Minnesota Real Estate	0.8599	0.2496	2	3

Comparing the results raises an important question: should model selection prioritize goodness of fit or theoretical consistency? While the overall fit can be visually assessed, modeling for policy analysis, especially when working with limited observations, may benefit more from the individual state-level models, as they align better with economic theory. For estimating forward-looking financial health of the farm economy and how federal agricultural policies change the level of financial well-being, economic rationale takes precedent over statistical fit.

With future policy analysis in mind, especially when projecting the impact of changes to key variables and with an emphasis on trying to assess regional impacts, the state-level variables seem to be the most practical option when analyzing the results. As more data becomes available, it's important to use models that not only fit the data well but also make economic sense. Following this logic, the panel regression models make the most sense as most of the variables were statistically significant and exhibited signs that aligned with economic theory.

Chapter 6 - Conclusions & Future Application

The agricultural industry has shown resiliency throughout time during tough economic conditions during the 1980's, the late 2000's, and during the late 2010's. Times of economic struggle for producers were seen in the Chapter 12 Bankruptcy filings from the U.S. courts and the loan delinquency data. There are plenty of ramifications for producers, policy makers, and credit lenders that the need for financial modeling on factors that impact farm delinquencies and ultimately farm bankruptcies. In this study we took the view through policy analysis with the idea to create baseline models that can potentially be used to help policy makers understand ramifications to producers due to potential changes in policy.

This study used three different modeling techniques: State Level Pooled Panel Regressions, State Level Individual State Regressions, and National Income and Expense Individual State models on each of the loan delinquency rate types, non-real estate and real estate. The state level models both behaved somewhat as expected with the pooled panel regression producing results almost completely as expected. Meanwhile, the national level models showed about half of the states do not behave as expected. Overall, the results from the models point to the panel model being the preferred model for modeling delinquency rates across the seven states analyzed. Overall, lagged delinquency rates emerged as the most significant coefficients. This finding reinforces the notion that financial stress, or well-being, among agricultural producers tends to persist year-over-year. The other variable that was generally statistically significant, and of the expected sign, was the lagged government payments variable.

This study is not without its weaknesses. The most glaring obstacle is the low number of observations. Next, the incorrect sign variables could be constrained to be of the correct sign forcing models to conform to economic and financial relationships. Third, a lack of granular data

to indicate which farm types are most at risk could not be modeled. While Key, Burns, and Lyons (2019) indicated that large farms were more at risk if farm incomes fell, the current research lacks access to data on farm-type differences. For example, the modeled delinquency rates for states like Kansas and Nebraska over the next few years are likely a result of a higher percentage of revenue from cattle, relative to crops, than for other states. Finally, the estimation of the Farm Credit and Commercial Bank delinquency rates could be challenged. Due to acquisitions, mergers, and the FCA changing the boundaries of each institution, estimating state-level delinquency rates accurately was challenging.

The panel models here present changes in delinquency rates as another data point policy makers and opinion leaders can use when assessing the change in the states of farm financial well-being as a result of proposed policy change. These models can prove useful to policymakers, producers, and lending institutions. In this study we determined the pooled state level models provide high statistical fit, make economic sense, and allow for painting a broad picture of what could happen to policy changes for these seven states.

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Appendix A: RaFF by State Variable Projections

Appendix Table A.1: RaFF Model Variable Table Projections (2024-2032)

Year	State	Unit	Real Crop Revenues (2024 Base Year)	Real Livestock Revenues (2024 Base Year)	Real Government Payment Revenues (2024 Base Year)	Real Total Expenses (2024 Base Year)
2024	Arkansas	Billion \$	\$4.83	\$7.24	\$0.42	\$10.19
2025	Arkansas	Billion \$	\$4.30	\$6.81	\$0.45	\$9.56
2026	Arkansas	Billion \$	\$4.14	\$6.50	\$0.44	\$9.09
2027	Arkansas	Billion \$	\$4.09	\$6.31	\$0.43	\$8.75
2028	Arkansas	Billion \$	\$4.03	\$6.13	\$0.39	\$8.44
2029	Arkansas	Billion \$	\$3.95	\$5.97	\$0.35	\$8.13
2030	Arkansas	Billion \$	\$3.85	\$5.79	\$0.32	\$7.84
2031	Arkansas	Billion \$	\$3.75	\$5.65	\$0.32	\$7.60
2032	Arkansas	Billion \$	\$3.65	\$5.51	\$0.31	\$7.41
2024	Illinois	Billion \$	\$19.04	\$3.48	\$0.71	\$19.10
2025	Illinois	Billion \$	\$16.87	\$3.51	\$0.84	\$18.04
2026	Illinois	Billion \$	\$16.11	\$3.34	\$1.10	\$17.19
2027	Illinois	Billion \$	\$15.71	\$3.24	\$1.10	\$16.74
2028	Illinois	Billion \$	\$15.38	\$3.08	\$1.04	\$16.33
2029	Illinois	Billion \$	\$14.94	\$2.93	\$0.68	\$15.91
2030	Illinois	Billion \$	\$14.45	\$2.80	\$0.59	\$15.50
2031	Illinois	Billion \$	\$13.96	\$2.71	\$0.57	\$15.15
2032	Illinois	Billion \$	\$13.55	\$2.65	\$0.56	\$14.88
2024	Iowa	Billion \$	\$18.37	\$18.37	\$1.23	\$32.71
2025	Iowa	Billion \$	\$16.79	\$18.69	\$1.33	\$31.25
2026	Iowa	Billion \$	\$16.01	\$18.40	\$1.58	\$30.24
2027	Iowa	Billion \$	\$15.57	\$18.03	\$1.56	\$29.66
2028	Iowa	Billion \$	\$15.19	\$17.31	\$1.50	\$29.04
2029	Iowa	Billion \$	\$14.72	\$16.59	\$1.12	\$28.33
2030	Iowa	Billion \$	\$14.20	\$16.01	\$1.02	\$27.61
2031	Iowa	Billion \$	\$13.69	\$15.58	\$0.99	\$27.00
2032	Iowa	Billion \$	\$13.26	\$15.31	\$0.97	\$26.53
2024	Kansas	Billion \$	\$8.08	\$15.63	\$0.69	\$23.59
2025	Kansas	Billion \$	\$8.31	\$15.93	\$0.47	\$22.67
2026	Kansas	Billion \$	\$7.89	\$15.70	\$0.56	\$21.75
2027	Kansas	Billion \$	\$7.63	\$15.10	\$0.61	\$20.88
2028	Kansas	Billion \$	\$7.40	\$14.26	\$0.61	\$19.98
2029	Kansas	Billion \$	\$7.13	\$13.40	\$0.42	\$19.11
2030	Kansas	Billion \$	\$6.84	\$12.64	\$0.42	\$18.30
2031	Kansas	Billion \$	\$6.56	\$12.11	\$0.41	\$17.68
2032	Kansas	Billion \$	\$6.31	\$11.67	\$0.41	\$17.15

Appendix Table B.1: RaFF Model Variable Table Projections (2024-2032) continued...

Year	State	Unit	Real Crop Revenues (2024 Base Year)	Real Livestock Revenues (2024 Base Year)	Real Government Payment Revenues (2024 Base Year)	Real Total Expenses (2024 Base Year)
2024	Minnesota	Billion \$	\$13.10	\$9.28	\$0.93	\$19.50
2025	Minnesota	Billion \$	\$12.04	\$9.40	\$0.84	\$18.44
2026	Minnesota	Billion \$	\$11.52	\$9.15	\$0.99	\$17.61
2027	Minnesota	Billion \$	\$11.22	\$8.86	\$1.01	\$17.10
2028	Minnesota	Billion \$	\$10.95	\$8.46	\$0.97	\$16.63
2029	Minnesota	Billion \$	\$10.63	\$8.07	\$0.75	\$16.12
2030	Minnesota	Billion \$	\$10.27	\$7.73	\$0.68	\$15.62
2031	Minnesota	Billion \$	\$9.92	\$7.48	\$0.66	\$15.19
2032	Minnesota	Billion \$	\$9.62	\$7.29	\$0.65	\$14.83
2024	Missouri	Billion \$	\$7.26	\$5.97	\$0.54	\$11.82
2025	Missouri	Billion \$	\$6.73	\$5.89	\$0.43	\$11.20
2026	Missouri	Billion \$	\$6.47	\$5.67	\$0.51	\$10.75
2027	Missouri	Billion \$	\$6.32	\$5.44	\$0.51	\$10.48
2028	Missouri	Billion \$	\$6.18	\$5.18	\$0.48	\$10.23
2029	Missouri	Billion \$	\$6.00	\$4.93	\$0.38	\$9.95
2030	Missouri	Billion \$	\$5.80	\$4.70	\$0.35	\$9.66
2031	Missouri	Billion \$	\$5.59	\$4.54	\$0.34	\$9.42
2032	Missouri	Billion \$	\$5.42	\$4.39	\$0.33	\$9.22
2024	Nebraska	Billion \$	\$12.62	\$17.62	\$0.68	\$27.19
2025	Nebraska	Billion \$	\$12.13	\$18.33	\$0.61	\$26.64
2026	Nebraska	Billion \$	\$11.58	\$18.25	\$0.80	\$25.80
2027	Nebraska	Billion \$	\$11.28	\$17.65	\$0.82	\$24.95
2028	Nebraska	Billion \$	\$11.01	\$16.76	\$0.79	\$23.99
2029	Nebraska	Billion \$	\$10.68	\$15.87	\$0.51	\$23.04
2030	Nebraska	Billion \$	\$10.30	\$15.01	\$0.47	\$22.14
2031	Nebraska	Billion \$	\$9.94	\$14.42	\$0.47	\$21.47
2032	Nebraska	Billion \$	\$9.63	\$13.94	\$0.46	\$20.90